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Gómez Gutiérrez et al.

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(54) **WIRELESS FEEDBACK CONTROL LOOPS WITH NEURAL NETWORKS TO PREDICT TARGET SYSTEM STATES**

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H04L 1/00 (2006.01)

(52) **U.S. Cl.**
CPC ***G06N 3/0445*** (2013.01); ***G06N 3/0454*** (2013.01); ***G06N 3/0472*** (2013.01); ***H04L 1/0081*** (2013.01)

(58) **Field of Classification Search**
CPC G06N 20/20; G06N 3/0454
See application file for complete search history.

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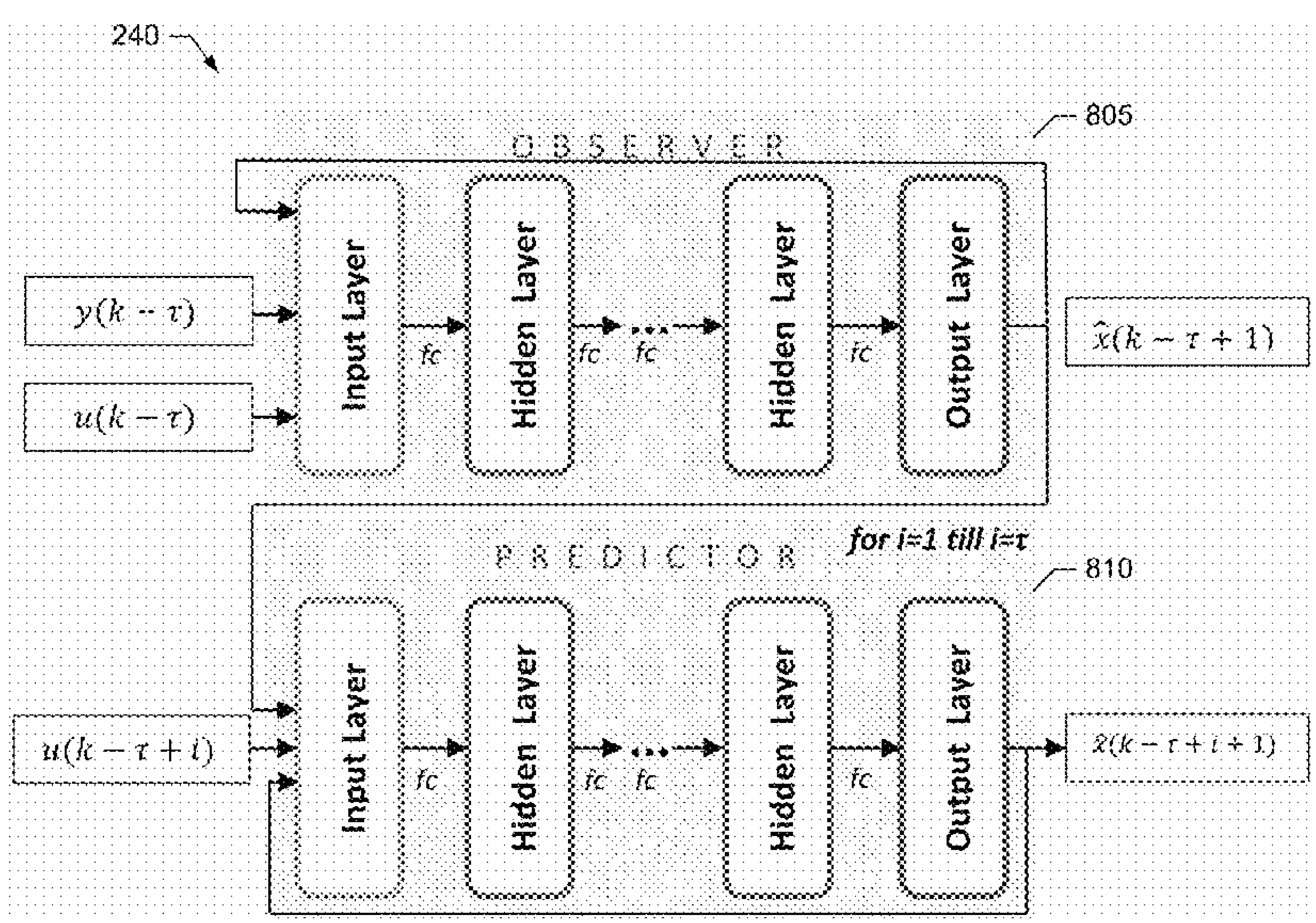
(57) **ABSTRACT**

Example wireless feedback control systems disclosed herein include a receiver to receive a first measurement of a target system via a first wireless link. Disclosed example systems also include a neural network to predict a value of a state of the target system at a future time relative to a prior time associated with the first measurement, the neural network to predict the value of the state of the target system based on the first measurement and a prior sequence of values of a control signal previously generated to control the target system during a time interval between the prior time and the future time, and the neural network to output the predicted value of the state of the target system to a controller. Disclosed example systems further include a transmitter to transmit a new value of the control signal to the target system via a second wireless link.

24 Claims, 17 Drawing Sheets



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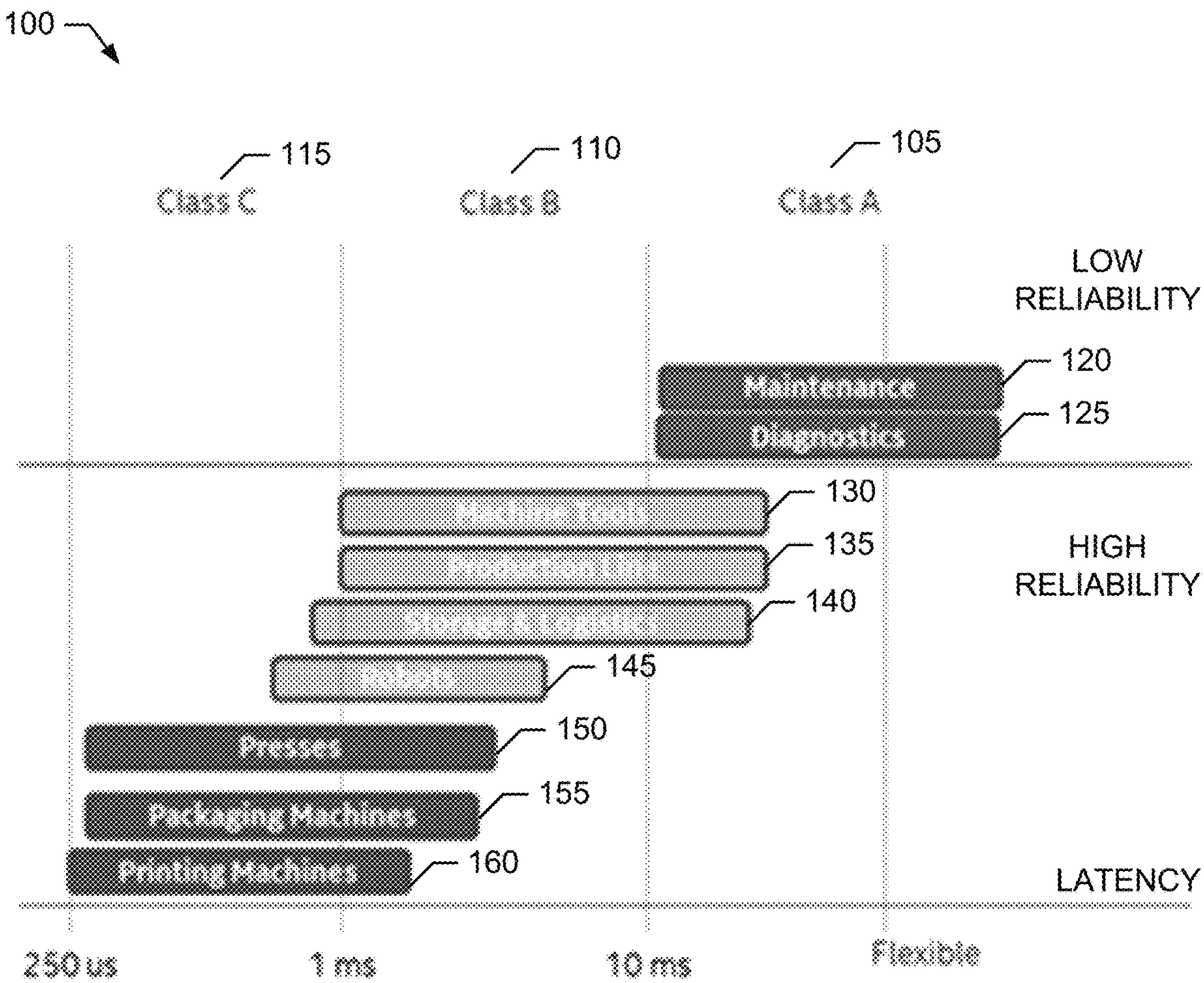

100
115
Class C
110
Class B
105
Class A
LOW
RELIABILITY
Maintenance
120
Diagnostics
125
130
135
HIGH
RELIABILITY
140
145
Presses
150
Packaging Machines
155
Printing Machines
160
LATENCY
250 us
1 ms
10 ms
Flexible

FIG. 1

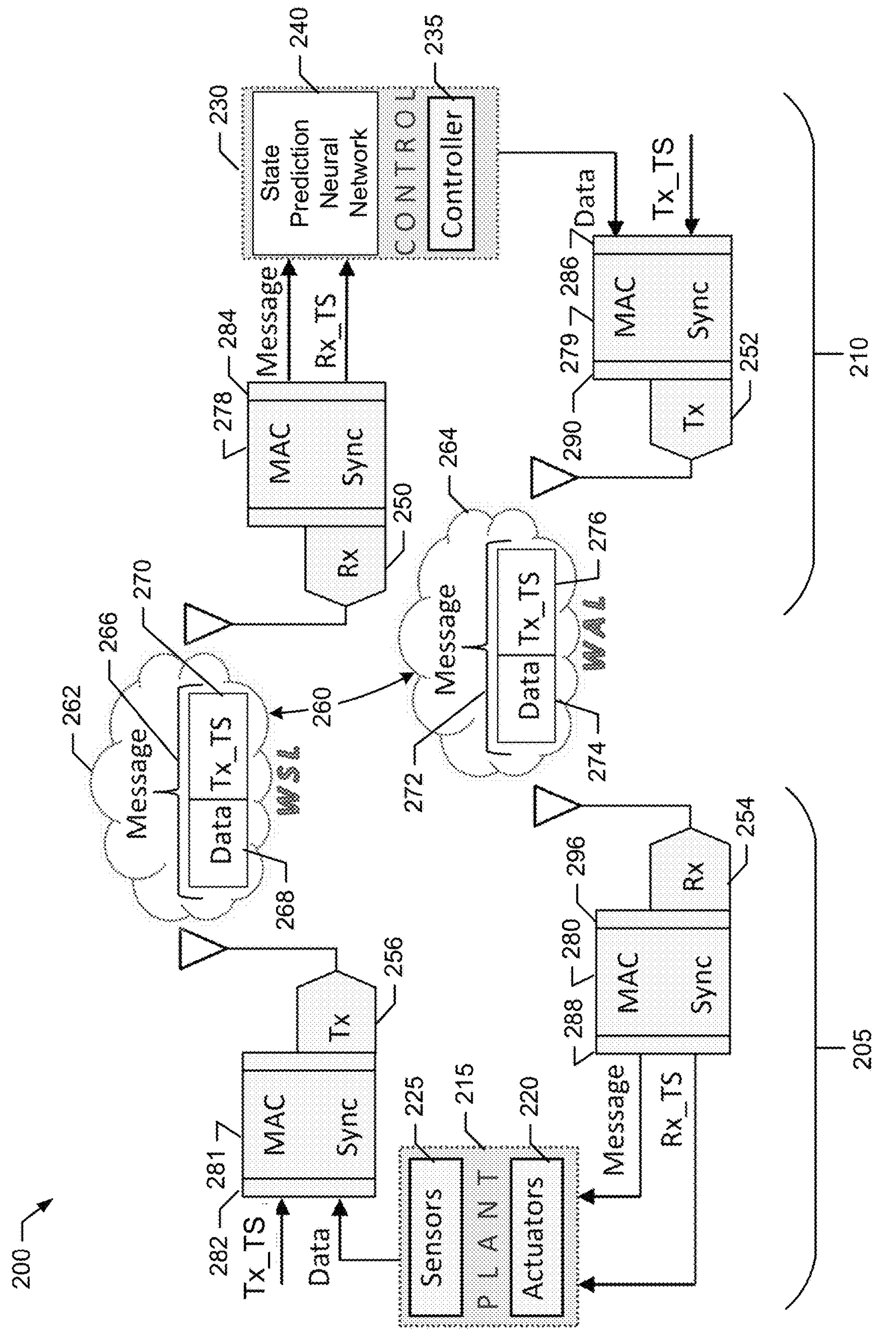
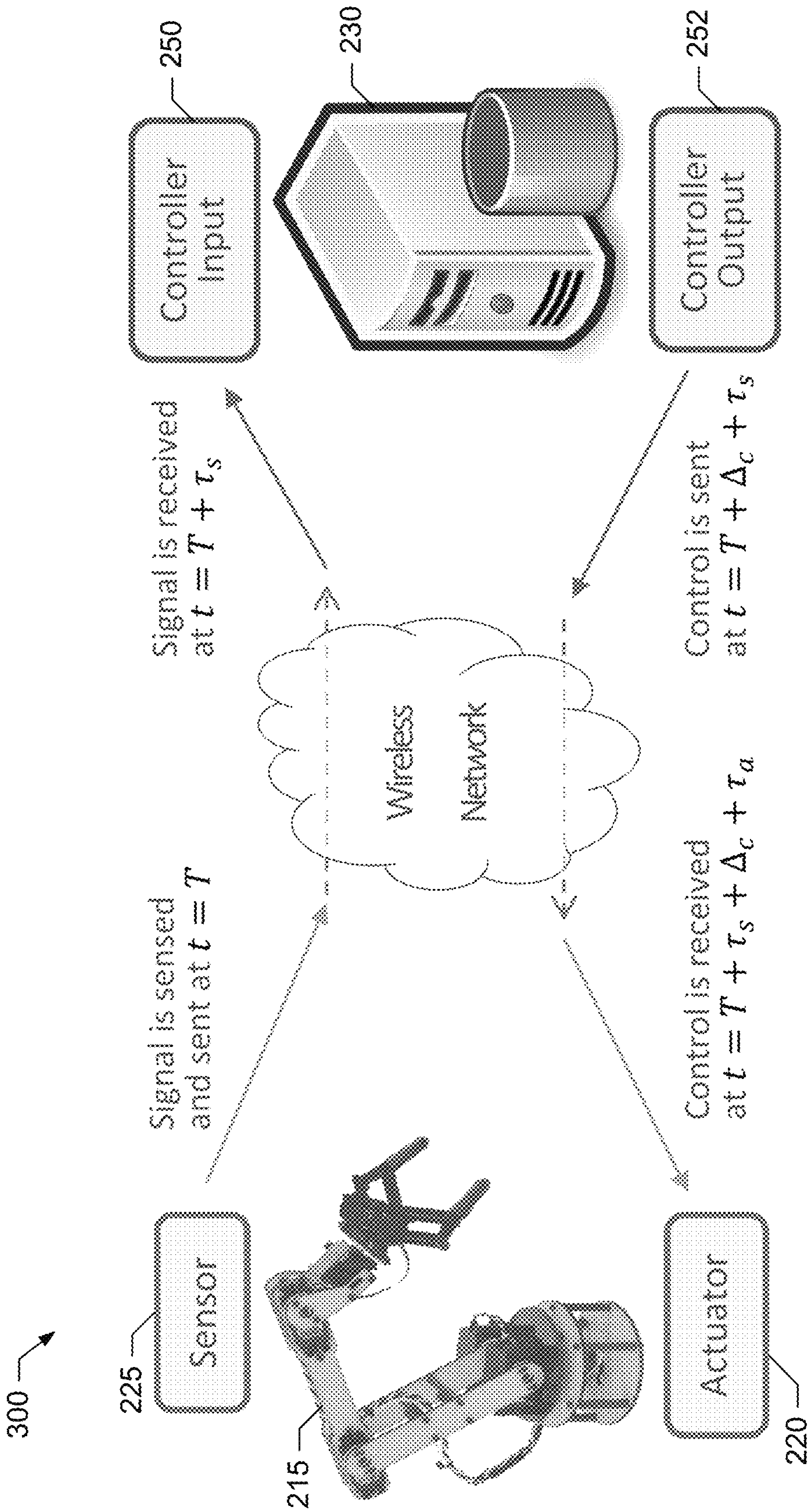

200
State Prediction Neural Network
CONTROL
Controller
PLANT
Sensors
Actuators
MAC
Sync
Tx
Rx
Message
Data
Tx_TS
Rx_TS
WSL
WAL
205
210
215
220
225
230
235
240
250
252
254
256
260
262
264
266
268
270
272
274
276
278
279
280
281
282
284
286
288
290
296

FIG. 2



300
225
Sensor
215
Actuator
220
Signal is sensed and sent at $t = T$
Wireless Network
Control is received at $t = T + \tau_s + \Delta_c + \tau_a$
Signal is received at $t = T + \tau_s$
Control is sent at $t = T + \Delta_c + \tau_s$
Controller Input
250
230
Controller Output
252

FIG. 3

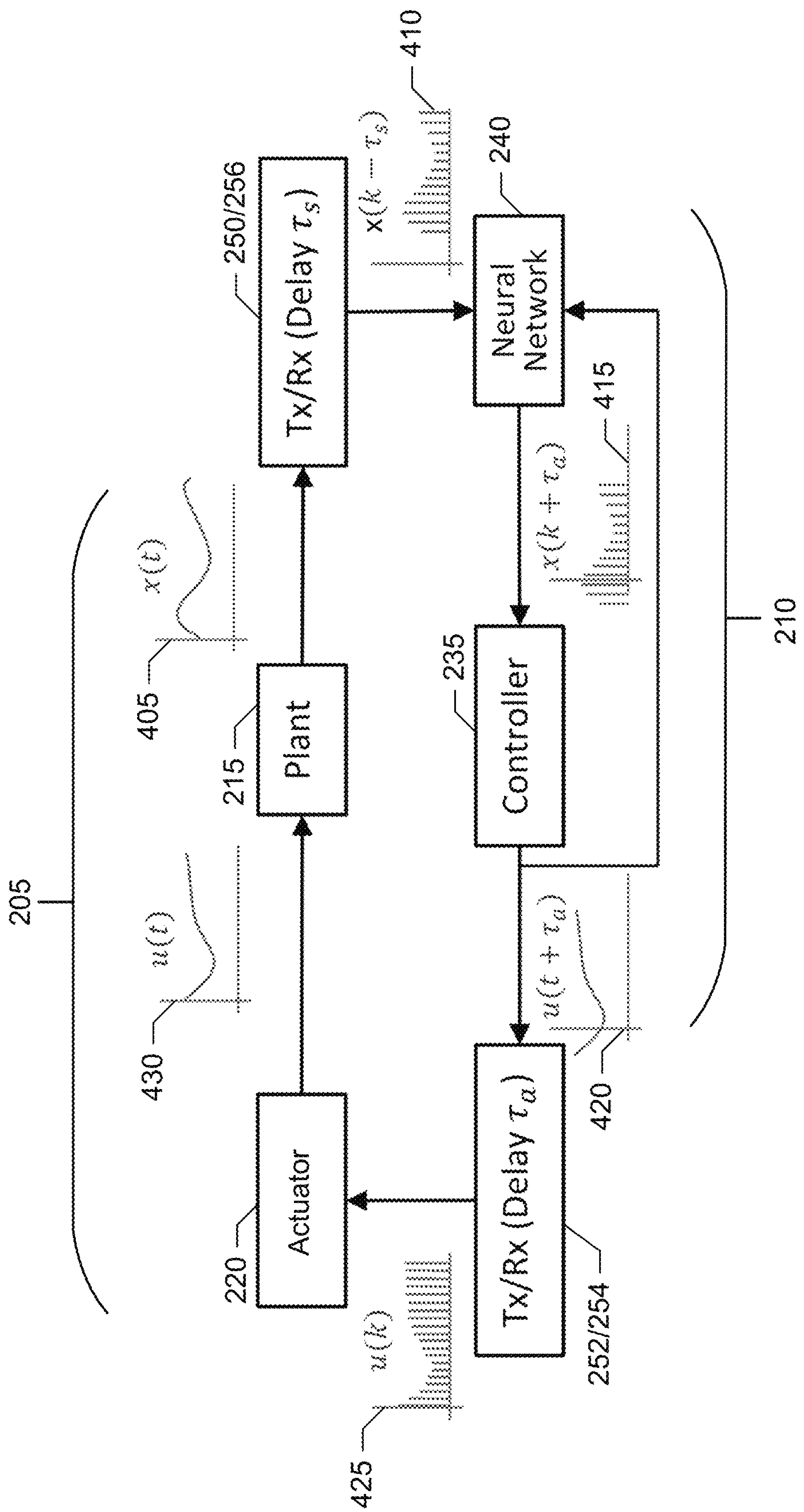

205
210
Tx/Rx (Delay τ_s)
250/256
Neural Network
240
$x(k-\tau_s)$
410
Plant
215
$x(t)$
405
Controller
235
$x(k+\tau_a)$
415
$u(t)$
430
$u(t+\tau_a)$
420
Actuator
220
Tx/Rx (Delay τ_a)
252/254
$u(k)$
425

FIG. 4

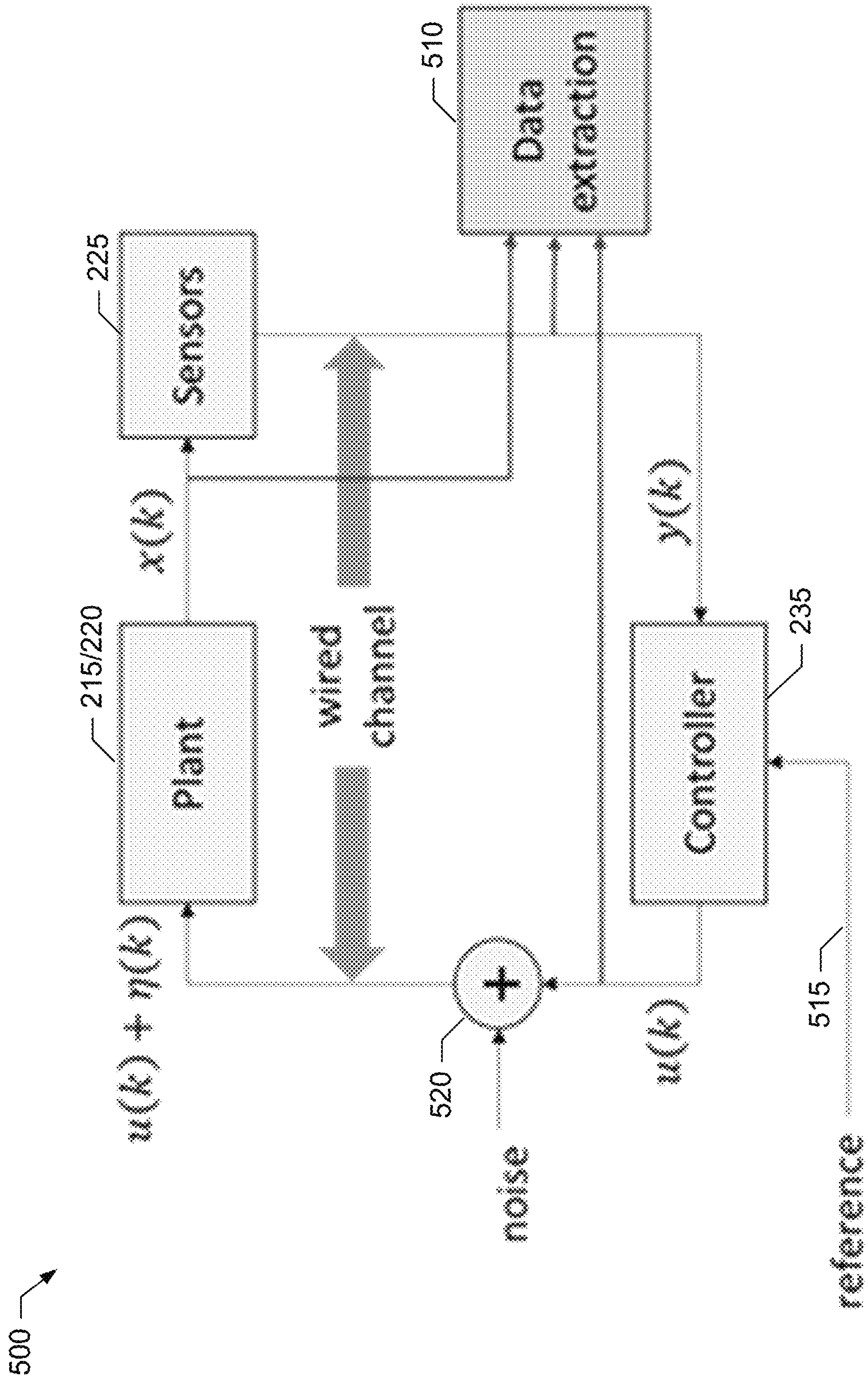

500
Plant
215/220
Sensors
225
Data extraction
510
wired channel
Controller
235
$x(k)$
$y(k)$
$u(k) + \eta(k)$
$u(k)$
noise
520
reference
515

FIG. 5

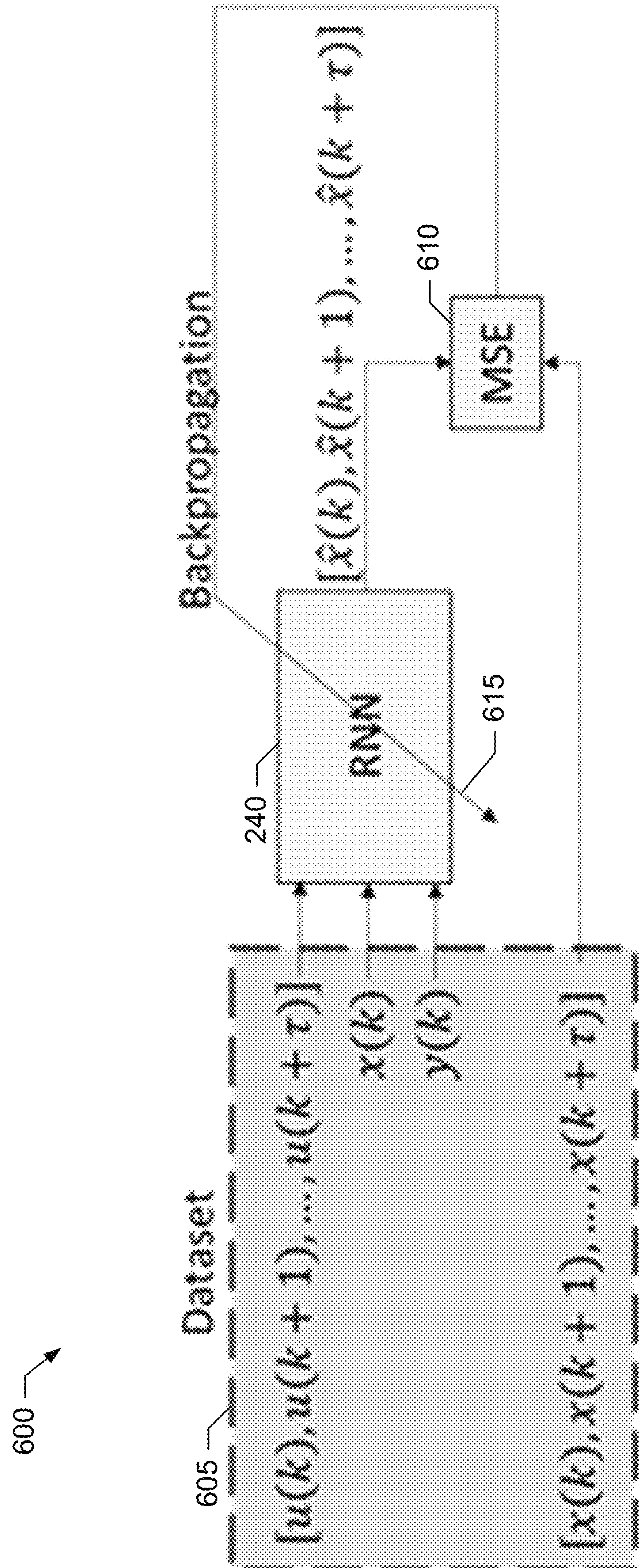

600
605
Dataset
$[u(k), u(k+1), \ldots, u(k+\tau)]$
$x(k)$
$y(k)$
$[x(k), x(k+1), \ldots, x(k+\tau)]$
240
RNN
615
Backpropagation
$[\hat{x}(k), \hat{x}(k+1), \ldots, \hat{x}(k+\tau)]$
610
MSE

FIG. 6

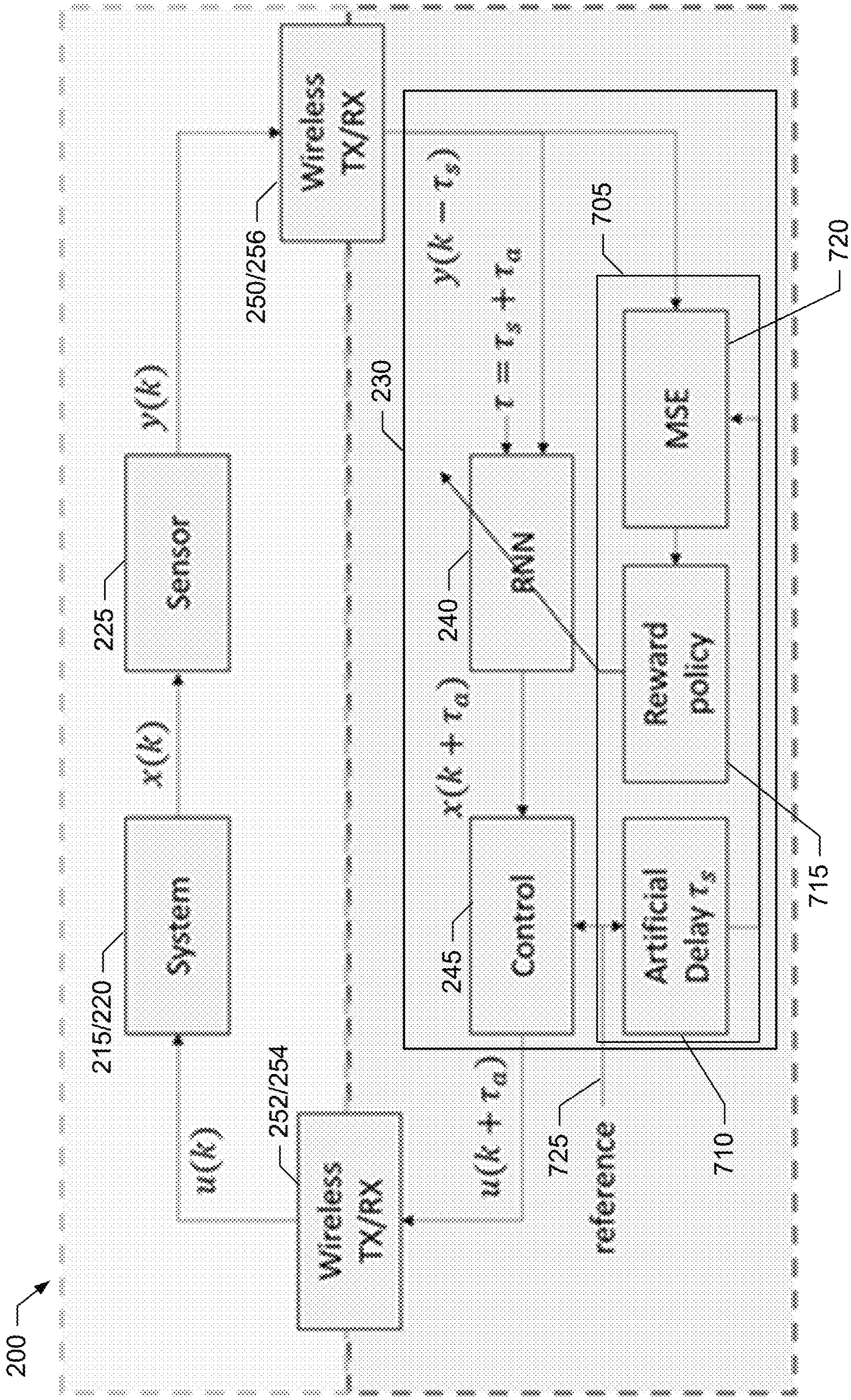

200
215/220
System
225
Sensor
$x(k)$
$y(k)$
250/256
Wireless TX/RX
$u(k)$
252/254
Wireless TX/RX
$u(k+\tau_a)$
725
reference
230
$y(k-\tau_s)$
$\tau=\tau_s+\tau_a$
240
RNN
$x(k+\tau_a)$
245
Control
705
MSE
720
Reward policy
715
Artificial Delay τ_s
710

FIG. 7

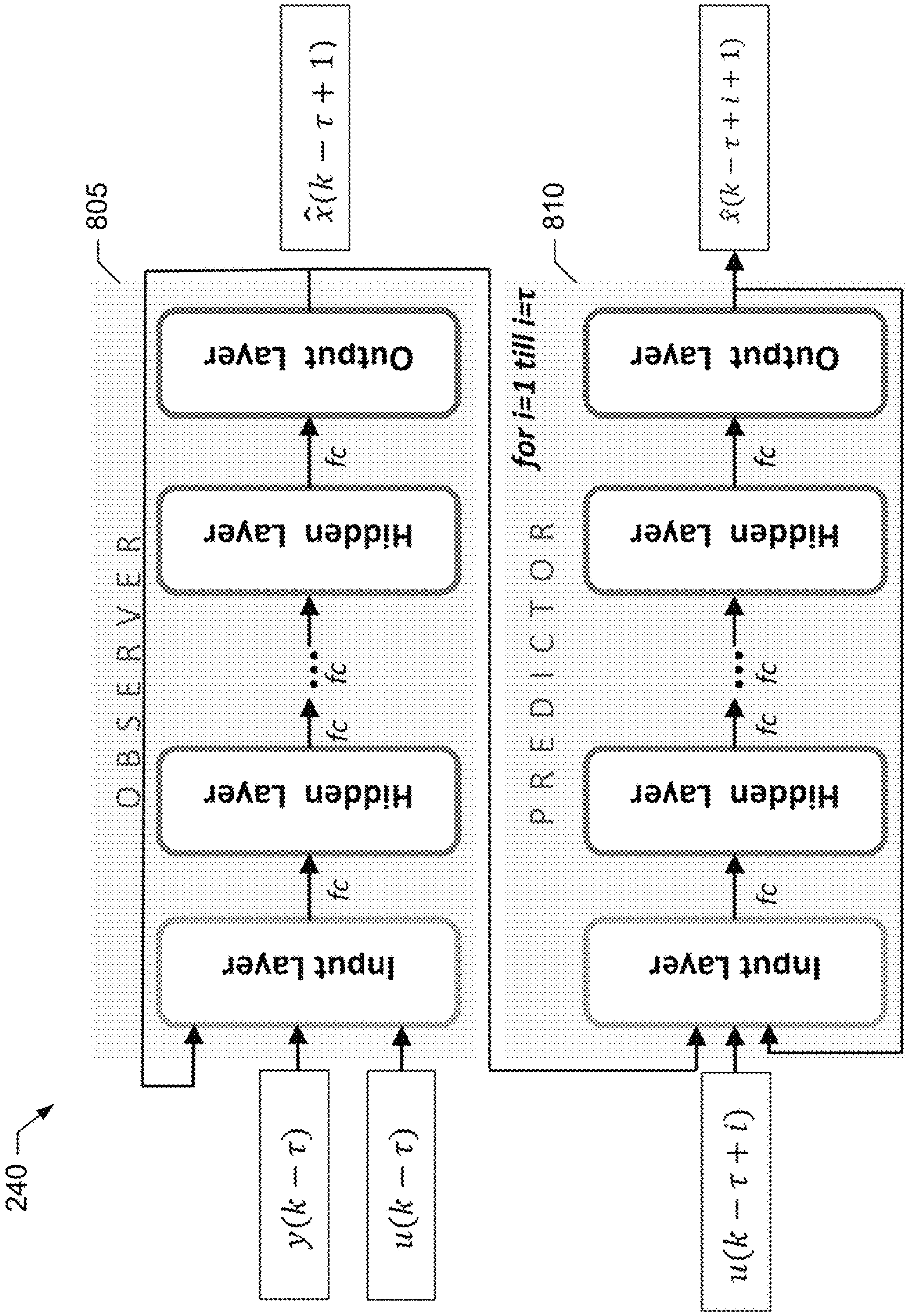

240
805
810
OBSERVER
PREDICTOR
$y(k-\tau)$
$u(k-\tau)$
Input Layer
fc
Hidden Layer
fc
...
fc
Hidden Layer
fc
Output Layer
$\hat{x}(k-\tau+1)$
for i=1 till i=τ
$u(k-\tau+i)$
Input Layer
fc
Hidden Layer
fc
...
fc
Hidden Layer
fc
Output Layer
$\hat{x}(k-\tau+i+1)$

FIG. 8

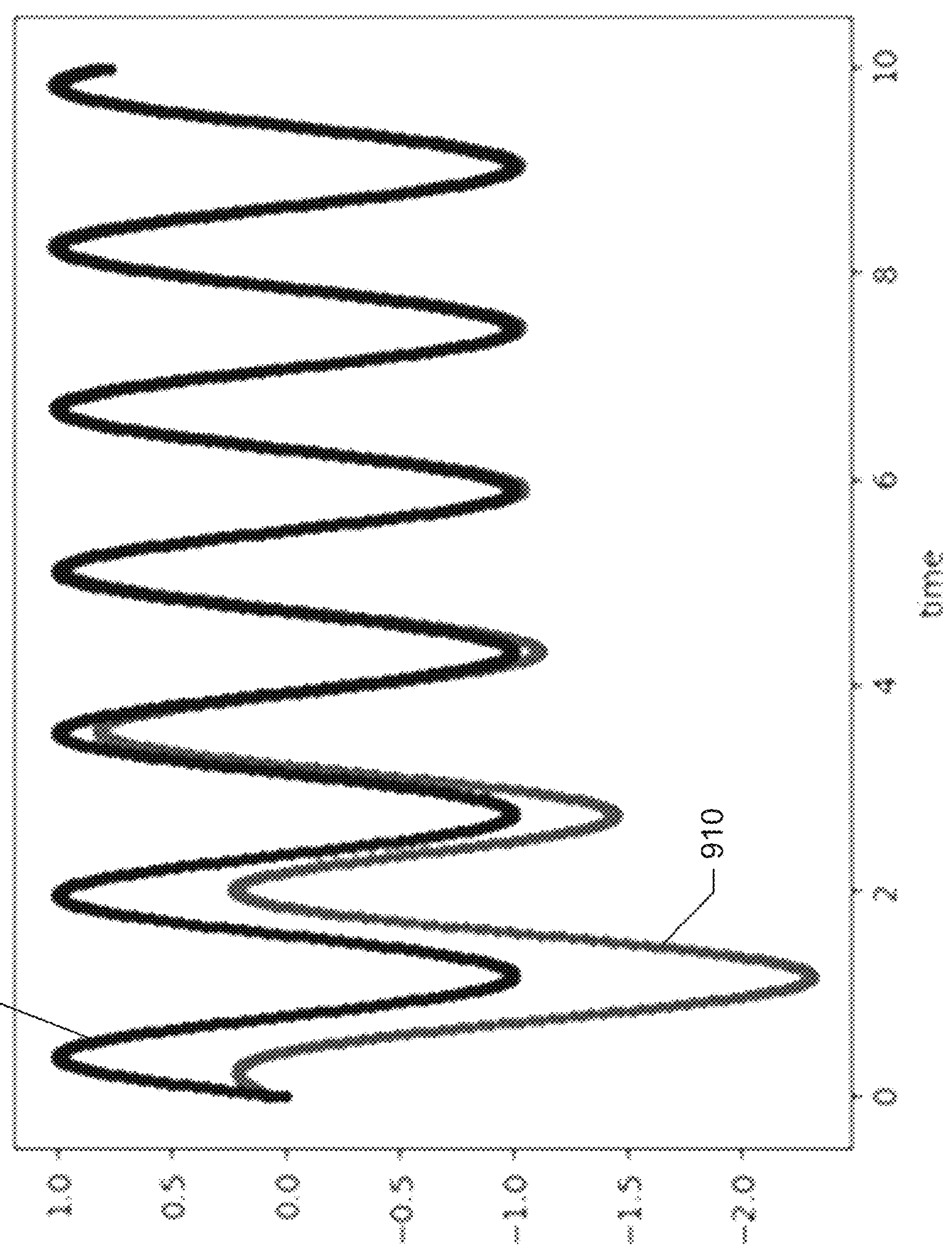


FIG. 9

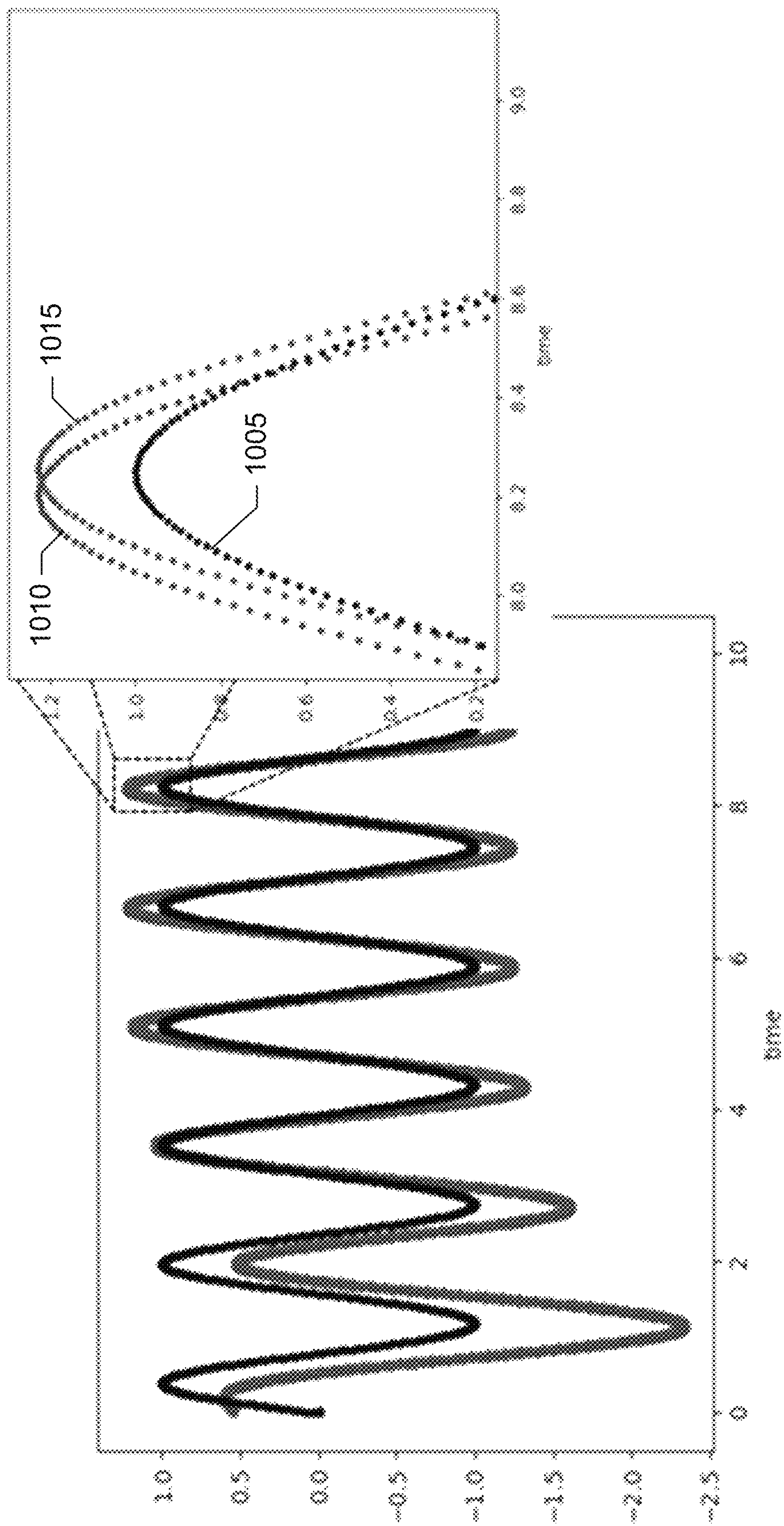


FIG. 10

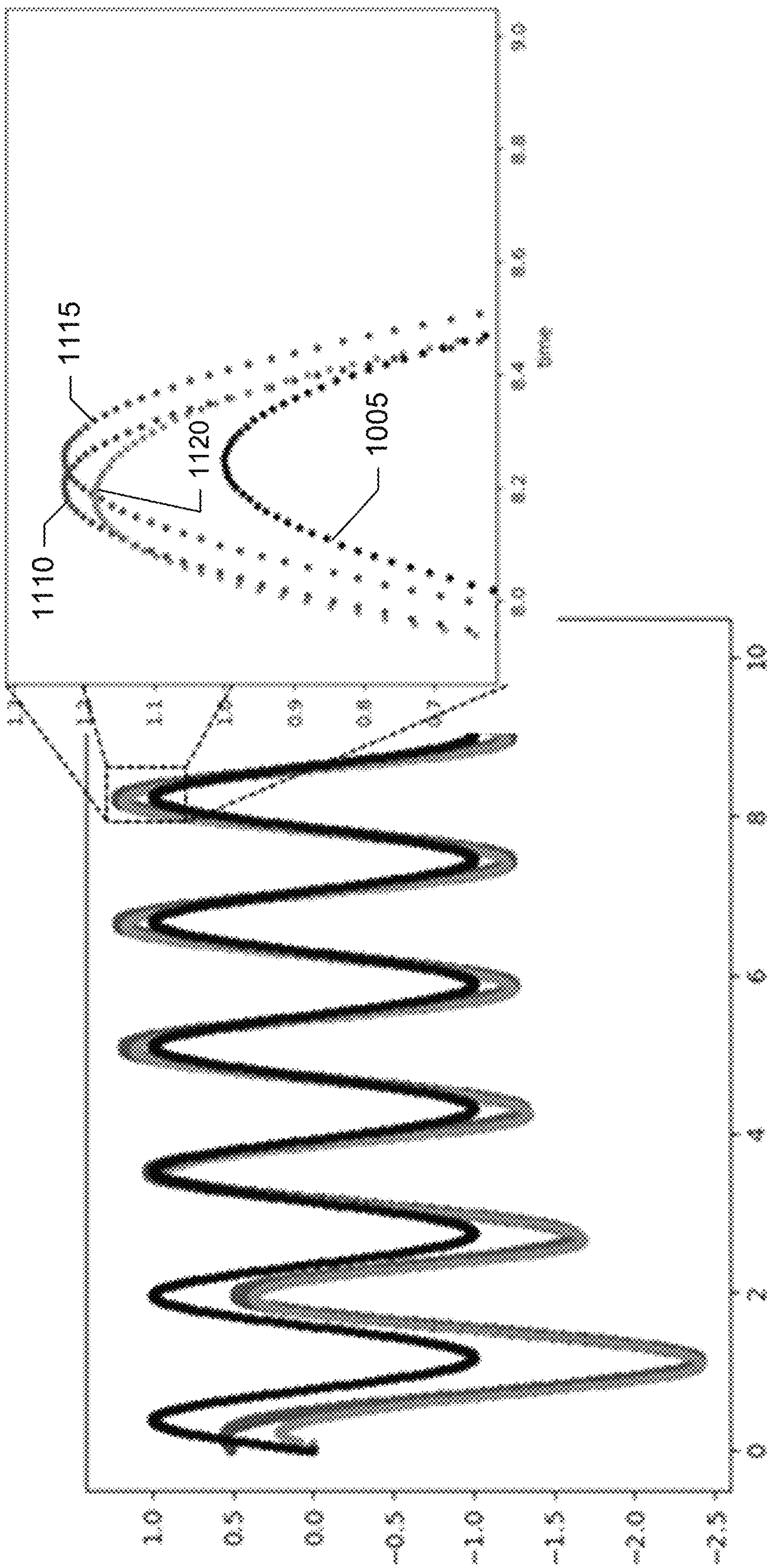


FIG. 11

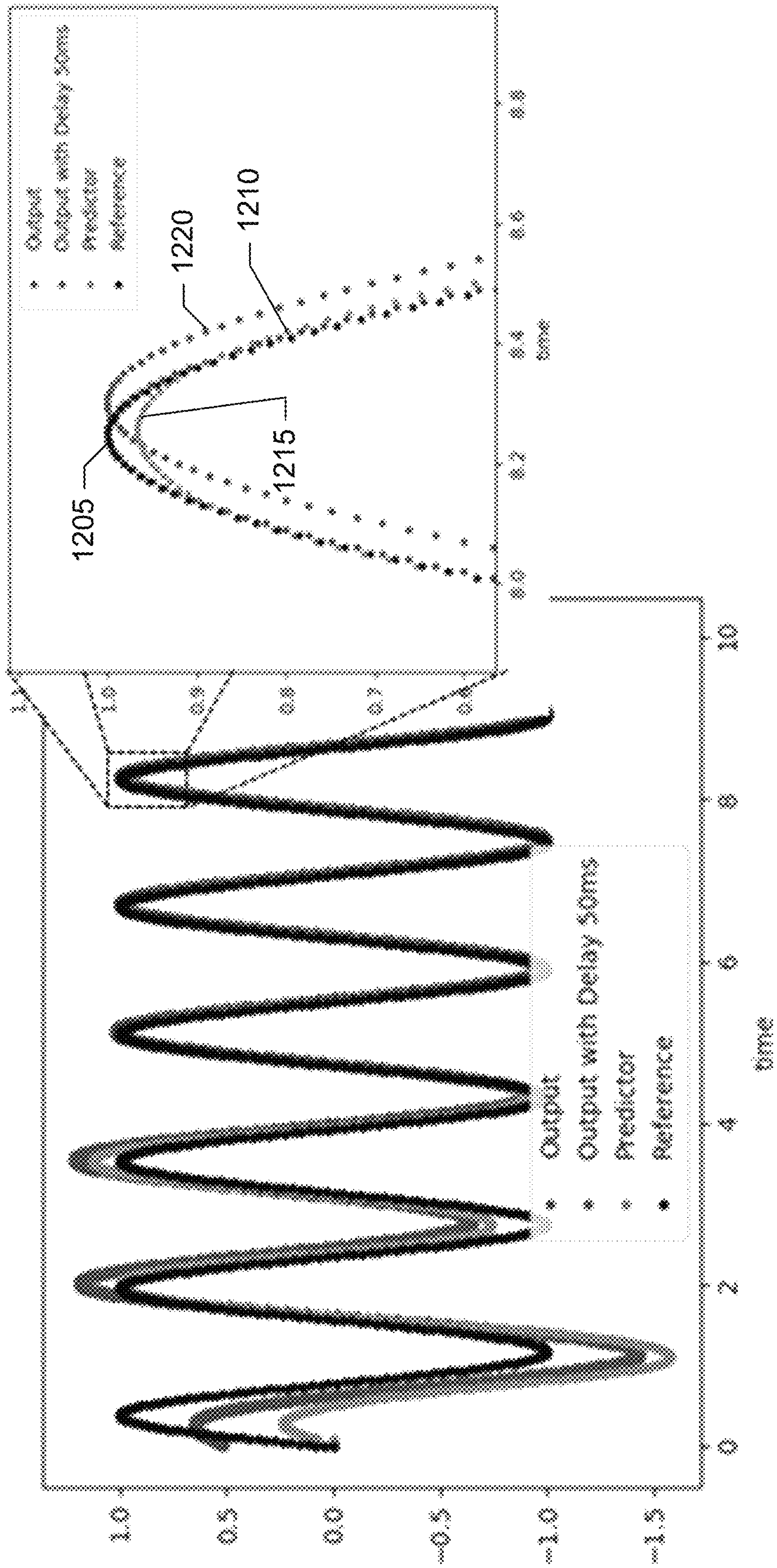

Output
Output with Delay 50ms
Predictor
Reference
time
1205
1210
1215
1220
1.0
0.5
0.0
−0.5
−1.0
−1.5
0
2
4
6
8
10

FIG. 12

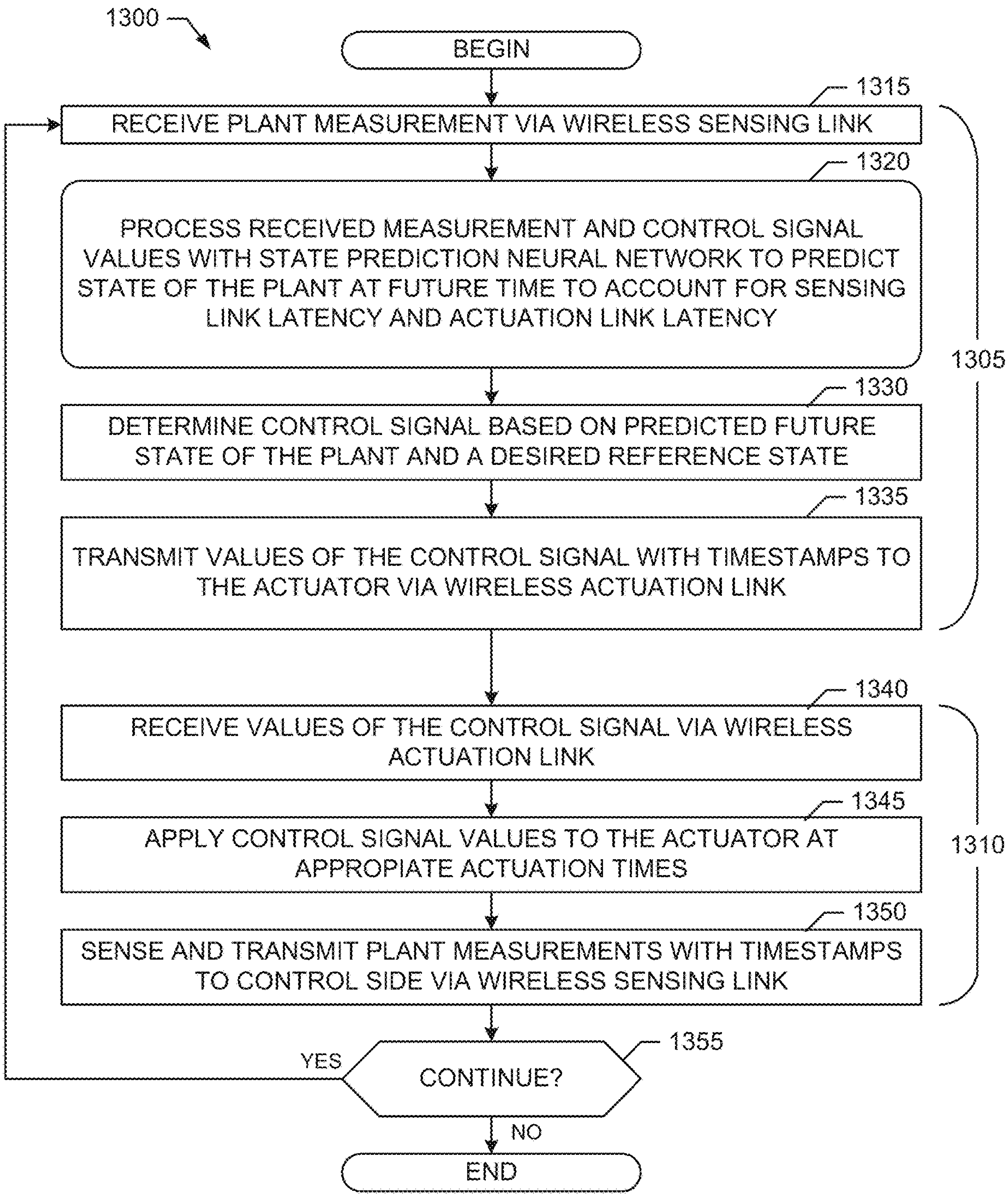

1300
BEGIN
1315
RECEIVE PLANT MEASUREMENT VIA WIRELESS SENSING LINK
1320
PROCESS RECEIVED MEASUREMENT AND CONTROL SIGNAL VALUES WITH STATE PREDICTION NEURAL NETWORK TO PREDICT STATE OF THE PLANT AT FUTURE TIME TO ACCOUNT FOR SENSING LINK LATENCY AND ACTUATION LINK LATENCY
1330
DETERMINE CONTROL SIGNAL BASED ON PREDICTED FUTURE STATE OF THE PLANT AND A DESIRED REFERENCE STATE
1335
TRANSMIT VALUES OF THE CONTROL SIGNAL WITH TIMESTAMPS TO THE ACTUATOR VIA WIRELESS ACTUATION LINK
1305
1340
RECEIVE VALUES OF THE CONTROL SIGNAL VIA WIRELESS ACTUATION LINK
1345
APPLY CONTROL SIGNAL VALUES TO THE ACTUATOR AT APPROPIATE ACTUATION TIMES
1350
SENSE AND TRANSMIT PLANT MEASUREMENTS WITH TIMESTAMPS TO CONTROL SIDE VIA WIRELESS SENSING LINK
1310
1355
YES
CONTINUE?
NO
END

FIG. 13

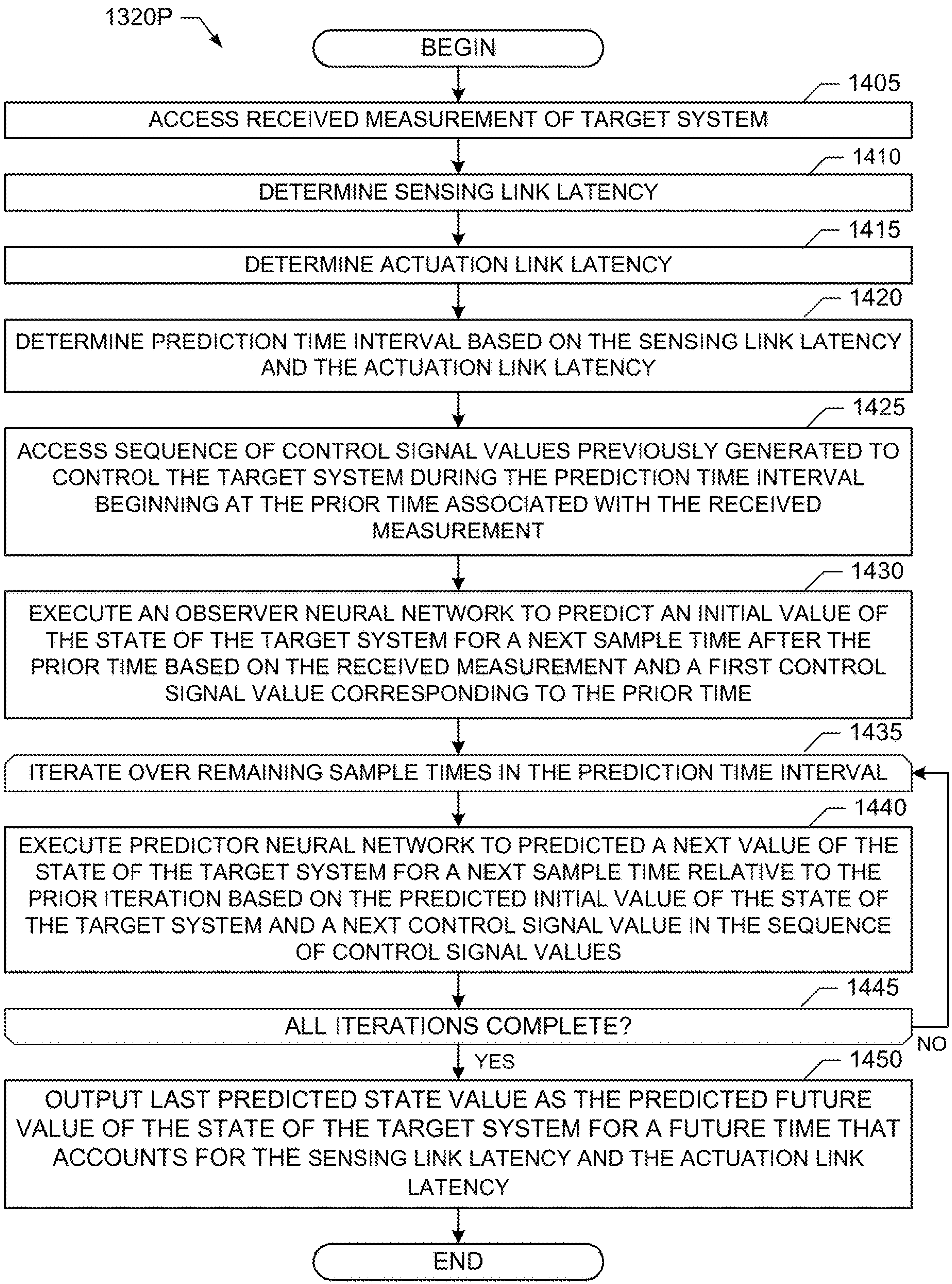

1320P
BEGIN
ACCESS RECEIVED MEASUREMENT OF TARGET SYSTEM
1405
DETERMINE SENSING LINK LATENCY
1410
DETERMINE ACTUATION LINK LATENCY
1415
DETERMINE PREDICTION TIME INTERVAL BASED ON THE SENSING LINK LATENCY AND THE ACTUATION LINK LATENCY
1420
ACCESS SEQUENCE OF CONTROL SIGNAL VALUES PREVIOUSLY GENERATED TO CONTROL THE TARGET SYSTEM DURING THE PREDICTION TIME INTERVAL BEGINNING AT THE PRIOR TIME ASSOCIATED WITH THE RECEIVED MEASUREMENT
1425
EXECUTE AN OBSERVER NEURAL NETWORK TO PREDICT AN INITIAL VALUE OF THE STATE OF THE TARGET SYSTEM FOR A NEXT SAMPLE TIME AFTER THE PRIOR TIME BASED ON THE RECEIVED MEASUREMENT AND A FIRST CONTROL SIGNAL VALUE CORRESPONDING TO THE PRIOR TIME
1430
ITERATE OVER REMAINING SAMPLE TIMES IN THE PREDICTION TIME INTERVAL
1435
EXECUTE PREDICTOR NEURAL NETWORK TO PREDICTED A NEXT VALUE OF THE STATE OF THE TARGET SYSTEM FOR A NEXT SAMPLE TIME RELATIVE TO THE PRIOR ITERATION BASED ON THE PREDICTED INITIAL VALUE OF THE STATE OF THE TARGET SYSTEM AND A NEXT CONTROL SIGNAL VALUE IN THE SEQUENCE OF CONTROL SIGNAL VALUES
1440
ALL ITERATIONS COMPLETE?
1445
NO
YES
OUTPUT LAST PREDICTED STATE VALUE AS THE PREDICTED FUTURE VALUE OF THE STATE OF THE TARGET SYSTEM FOR A FUTURE TIME THAT ACCOUNTS FOR THE SENSING LINK LATENCY AND THE ACTUATION LINK LATENCY
1450
END

FIG. 14

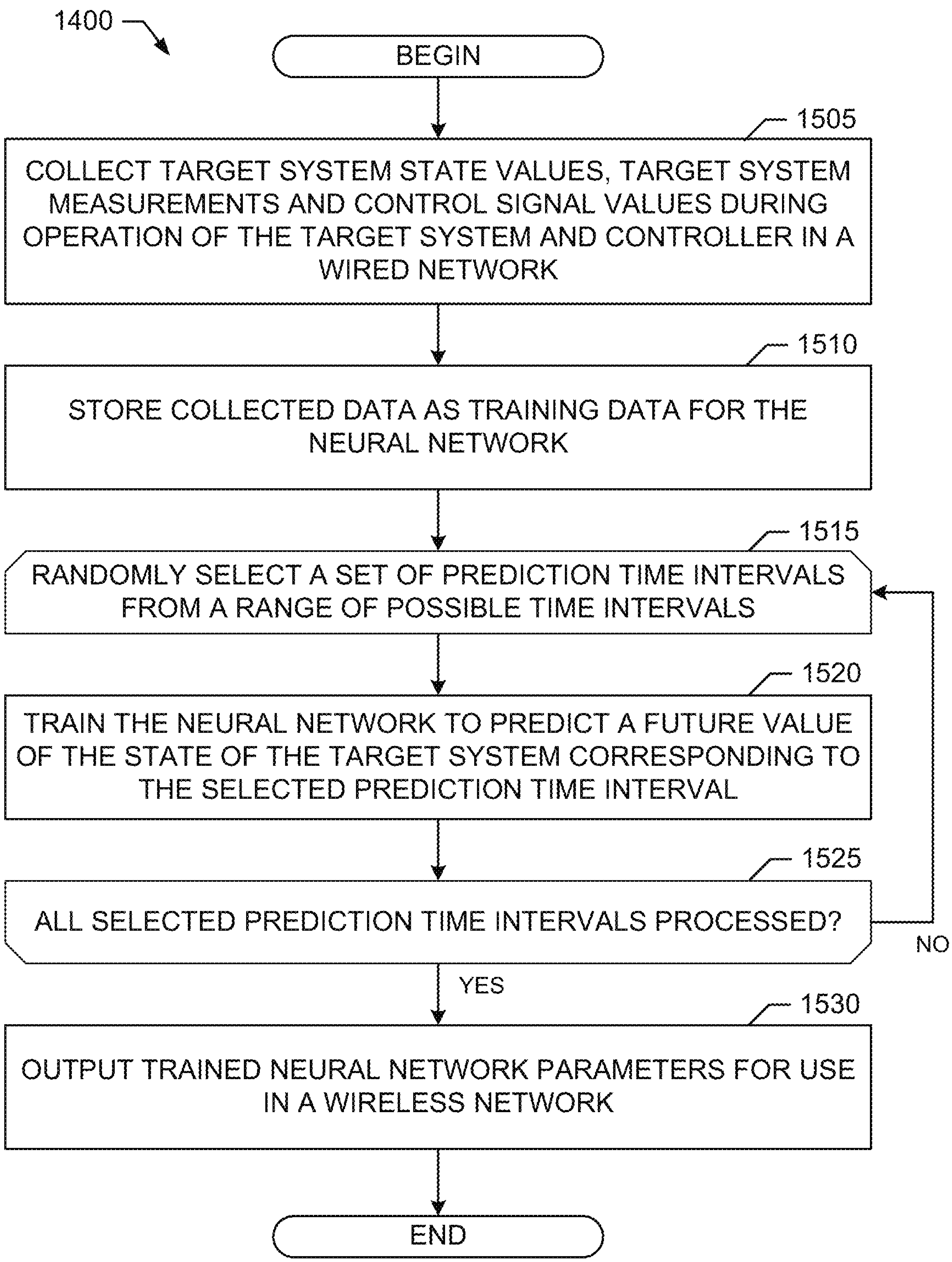

1400
BEGIN
1505
COLLECT TARGET SYSTEM STATE VALUES, TARGET SYSTEM MEASUREMENTS AND CONTROL SIGNAL VALUES DURING OPERATION OF THE TARGET SYSTEM AND CONTROLLER IN A WIRED NETWORK
1510
STORE COLLECTED DATA AS TRAINING DATA FOR THE NEURAL NETWORK
1515
RANDOMLY SELECT A SET OF PREDICTION TIME INTERVALS FROM A RANGE OF POSSIBLE TIME INTERVALS
1520
TRAIN THE NEURAL NETWORK TO PREDICT A FUTURE VALUE OF THE STATE OF THE TARGET SYSTEM CORRESPONDING TO THE SELECTED PREDICTION TIME INTERVAL
1525
ALL SELECTED PREDICTION TIME INTERVALS PROCESSED?
NO
YES
1530
OUTPUT TRAINED NEURAL NETWORK PARAMETERS FOR USE IN A WIRELESS NETWORK
END

FIG. 15

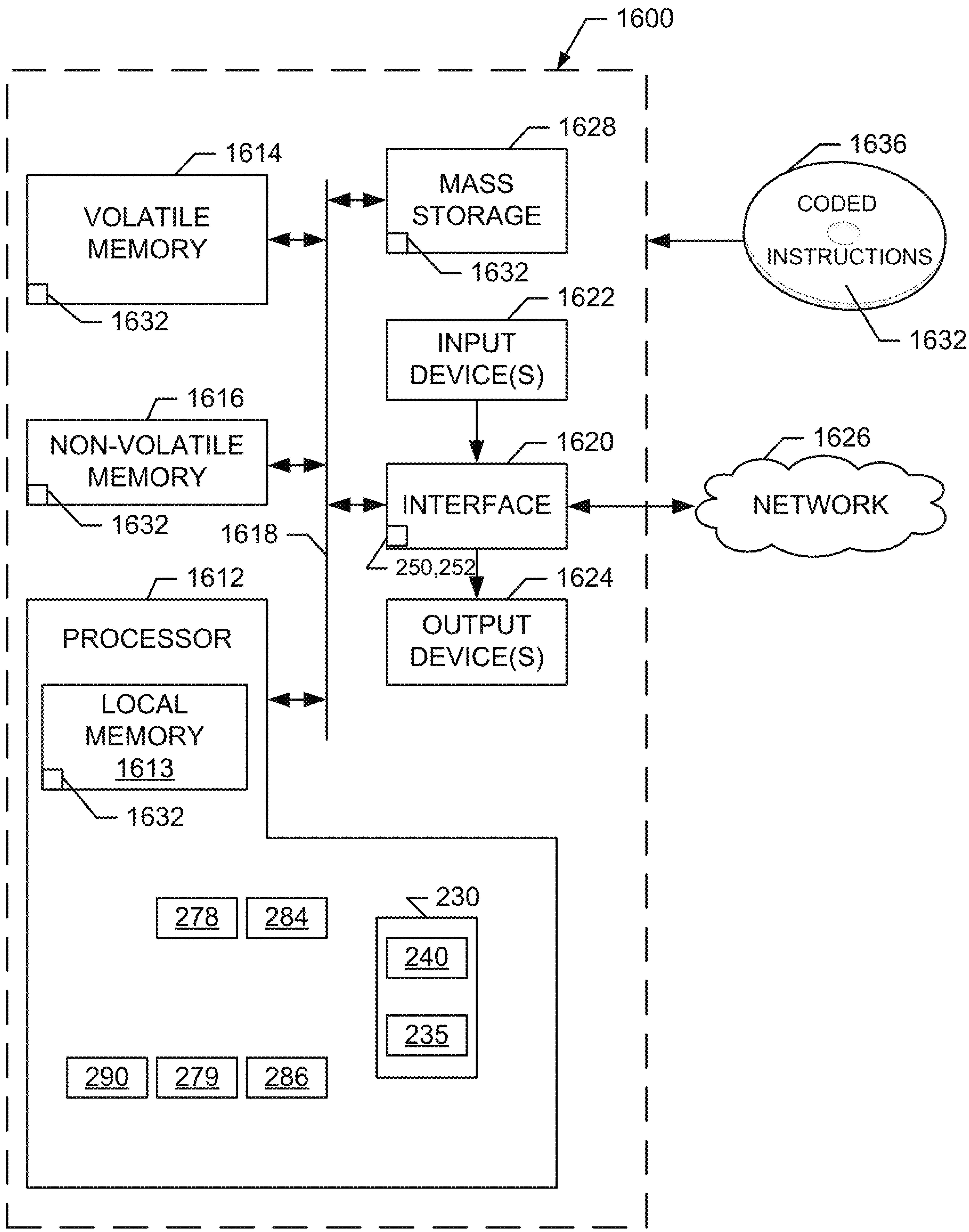

1600
1614
VOLATILE MEMORY
1632
1628
MASS STORAGE
1632
1636
CODED INSTRUCTIONS
1632
1622
INPUT DEVICE(S)
1616
NON-VOLATILE MEMORY
1632
1620
INTERFACE
1626
NETWORK
1618
250,252
1624
OUTPUT DEVICE(S)
1612
PROCESSOR
LOCAL MEMORY 1613
1632
278
284
230
240
235
290
279
286

FIG. 16

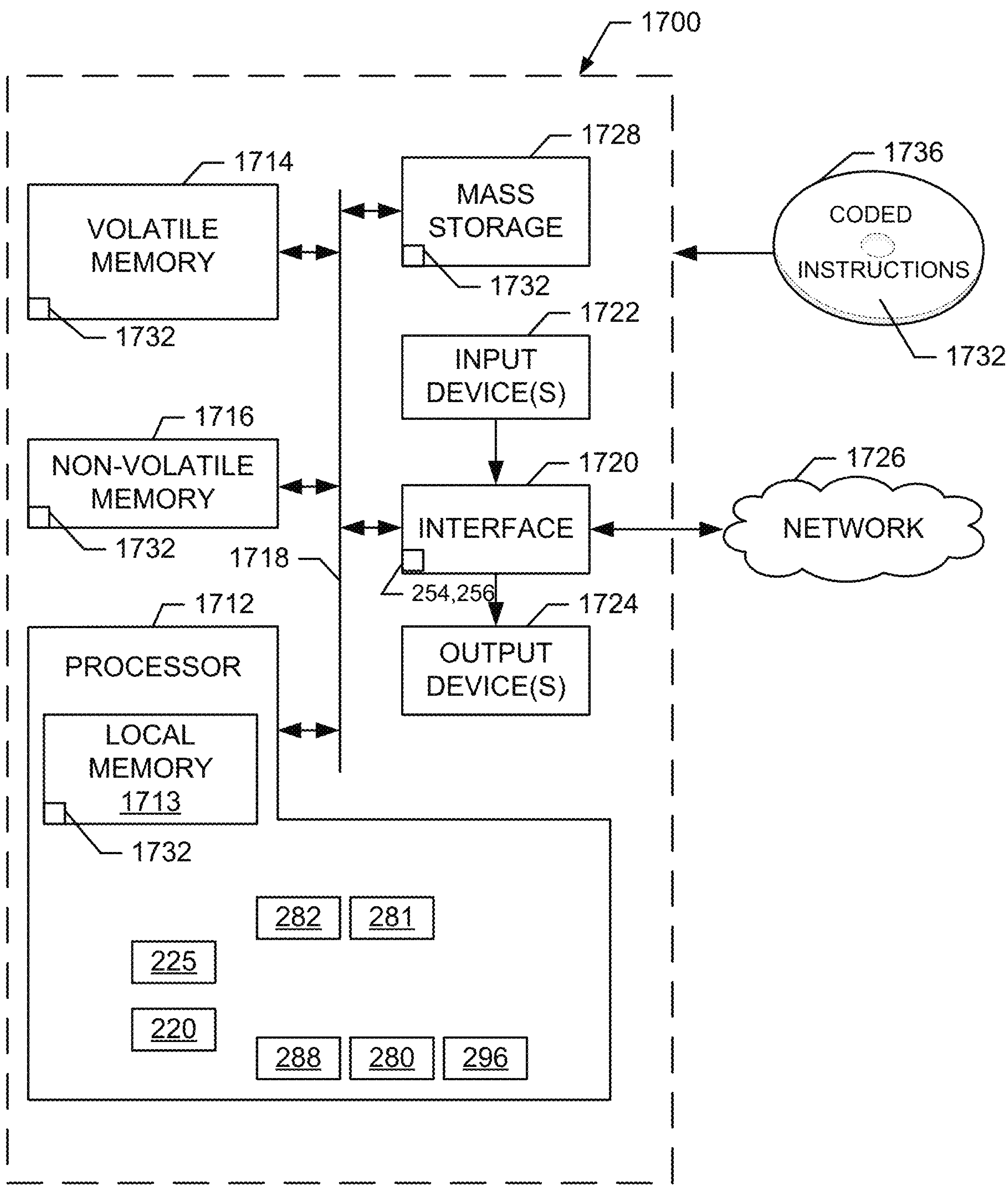

1700
1714
VOLATILE MEMORY
1732
1728
MASS STORAGE
1732
1736
CODED INSTRUCTIONS
1732
1722
INPUT DEVICE(S)
1716
NON-VOLATILE MEMORY
1732
1718
1720
INTERFACE
254,256
1726
NETWORK
1712
PROCESSOR
LOCAL MEMORY 1713
1732
1724
OUTPUT DEVICE(S)
282
281
225
220
288
280
296

FIG. 17

WIRELESS FEEDBACK CONTROL LOOPS WITH NEURAL NETWORKS TO PREDICT TARGET SYSTEM STATES

FIELD OF THE DISCLOSURE

This disclosure relates generally to control loops and, more particularly, to wireless feedback control loops with neural networks to predict target system states.

BACKGROUND

Feedback control systems in industrial applications typically include a controller to generate a control signal to be applied to an actuator, which is to adjust an input of a target system, such as a plant, being controlled. The controller generates the control signal based on one or more measured outputs of the plant and reference value(s) that represent the corresponding desired output(s) of the plant. Prior feedback control systems often rely on wired networks to convey the control signal from the controller to the actuator, and to convey the measured output(s) of the plant to the controller.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1** is a graph illustrating example latency and reliability requirements for different types of industrial systems to be controlled by a feedback control system.

FIG. **2** is a block diagram of an example predictive wireless feedback control system including an example state prediction neural network, both of which are implemented in accordance with teachings of this disclosure.

FIG. **3** illustrates example wireless network link latencies in the example predictive wireless feedback control system of FIG. **2**

FIG. **4** illustrates an example operation of the example predictive wireless feedback control system of FIG. **2**.

FIG. **5** is a block diagram of an example system to collect training data to be used to train the example state prediction neural network of FIG. **2**.

FIG. **6** illustrates an example training procedure that may be used to train the example state prediction neural network of FIG. **2**.

FIGS. **7**-**8** illustrate example implementations of the state prediction neural network of FIG. **2**

FIGS. **9**-**12** illustrate example operational results obtained by the example predictive wireless feedback control system of FIG. **2**.

FIG. **13** is a flowchart representative of example computer readable instructions that may be executed to implement the example predictive wireless feedback control system of FIG. **2**.

FIG. **14** is a flowchart representative of example computer readable instructions that may be executed to implement the example state prediction neural network of FIGS. **2**, **7** and/or **8**.

FIG. **15** is a flowchart representative of example computer readable instructions that may be executed to train the example state prediction neural network of FIGS. **2**, **7** and/or **8**.

FIG. **16** is a block diagram of an example processor platform structured to execute the example computer readable instructions of FIGS. **11**, **12** and/or **13** to implement control-side processing in the example predictive wireless feedback control system of FIG. **2**.

FIG. **17** is a block diagram of an example processor platform structured to execute the example computer readable instructions of FIG. **11** to implement target-side processing in the example predictive wireless feedback control system of FIG. **2**.

The figures are not to scale. In general, the same reference numbers will be used throughout the drawing(s) and accompanying written description to refer to the same or like parts, elements, etc. Connection references (e.g., attached, coupled, connected, and joined) are to be construed broadly and may include intermediate members between a collection of elements and relative movement between elements unless otherwise indicated. As such, connection references do not necessarily infer that two elements are directly connected and in fixed relation to each other.

Descriptors "first," "second," "third," etc. are used herein when identifying multiple elements or components which may be referred to separately. Unless otherwise specified or understood based on their context of use, such descriptors are not intended to impute any meaning of priority, physical order or arrangement in a list, or ordering in time but are merely used as labels for referring to multiple elements or components separately for ease of understanding the disclosed examples. In some examples, the descriptor "first" may be used to refer to an element in the detailed description, while the same element may be referred to in a claim with a different descriptor such as "second" or "third." In such instances, it should be understood that such descriptors are used merely for ease of referencing multiple elements or components.

DETAILED DESCRIPTION

Example methods, apparatus, systems and articles of manufacture (e.g., physical storage media) to implement wireless feedback control loops with neural networks to predict target system states are disclosed herein. Example wireless feedback control systems disclosed herein include a receiver to receive a first measurement of a target system via a wireless sensing link (e.g., a first wireless link). Disclosed example systems also include a neural network to predict a value of a state of the target system at a future time relative to a prior time associated with the first measurement. In some disclosed examples, a time interval between the prior time and the future time is based on a first latency of the wireless sensing link and a second latency associated with a wireless actuation link (e.g., a second wireless link). In some disclosed examples, the neural network is to predict the value of the state of the target system based on the first measurement and a prior sequence of values of a control signal previously generated to control the target system during the time interval between the prior time and the future time. In some disclosed examples, the neural network is also to output the predicted value of the state of the target system to a controller that is to generate a new value of the control signal. Disclosed example systems further include a transmitter to transmit the new value of the control signal to the target system via the wireless actuation link.

In some example wireless feedback control systems disclosed herein, the receiver is a first receiver, the transmitter is a first transmitter, and the wireless sensing link and the wireless actuation link are implemented by a wireless time sensitive network. In some disclosed examples, the wireless time sensitive network is to provide time synchronization between the first receiver and a second transmitter that is to transmit the first measurement of the target system to the first receiver via the wireless sensing link. Additionally or alternatively, in some disclosed examples, the wireless time sensitive network is to provide time synchronization between the first transmitter and a second receiver that is to receive the new value of the control signal transmitted by the first transmitter via the wireless actuation link.

In some such disclosed example wireless feedback control systems, the first receiver is to receive the first measurement in a message from the second transmitter via the wireless sensing link. In some such disclosed examples, the message is to include a timestamp to identify a first time at which the second transmitter transmitted the message, and the first receiver is to determine the first latency of the wireless sensing link based on the timestamp and a second time at which the first receiver received the message.

Additionally or alternatively, in some such disclosed example wireless feedback control systems, the first transmitter is to transmit a first one of the prior sequence of values of the control signal in a message to the second receiver via the wireless actuation link. In some such disclosed examples, the message is to include a timestamp to identify a first time at which the first transmitter transmitted the message, and the first transmitter to determine the second latency associated with the wireless actuation link based on a report from the second receiver in response to the message. In some such disclosed examples, the second latency associated with the wireless sensing link corresponds to at least one of a maximum latency of the wireless actuation link, a minimum latency of the wireless actuation link, an average latency for the wireless actuation link, or a probabilistic latency value for the wireless actuation link.

In some example wireless feedback control systems disclosed herein, the time interval between the prior time and the future time is sampled to include a first number of sample times, the predicted value of the state of the target system is a first predicted value, and the neural network includes a first neural network in communication with a second neural network. In some disclosed examples, the first neural network is trained to predict a second predicted value of the state of the target system based on the first measurement and a first one of the prior sequence of values of the control signal corresponding to a first sample time representative of the prior time. In some disclosed examples, the second predicted value of the state of the target system corresponds to one sample time after the first sample time. In some disclosed examples, the second neural network is to predict the first predicted value of the state of the target system based on the second predicted value of the state of the target system and remaining ones of the sequence of values of the control signal corresponding to ones of the first number of samples times after the first sample time.

In some such disclosed example wireless feedback control systems, the second neural network is to predict multiple predicted values of the state of the target system corresponding respectively to respective sample times between the second predicted value and the first predicted value. In some disclosed examples, the second neural network is to predict respective ones of the multiple predicted values iteratively based on application of the remaining ones of the sequence of values of the control signal sequentially to the second neural network.

Some example wireless feedback control systems disclosed herein further include a neural network updater to update the neural network based on an error between the first measurement and a delayed reference value. In some disclosed examples, the delayed reference value is representative of a target state of the target system corresponding to the prior time associated with the first measurement.

These and other example methods, apparatus, systems and articles of manufacture (e.g., physical storage media) to implement wireless feedback control loops with neural networks to predict target system states are disclosed in further detail below.

As mentioned above, prior feedback control systems often rely on wired networks to convey a control signal from a controller to an actuator that is to adjust an input of the system being controlled, such as a plant or, more generally, any controlled system, such as those listed in FIG. **1**. Such prior feedback control systems may also rely on wired networks to convey one or more measured outputs of the controlled system back to the controller, which uses the measured output(s) and reference value(s) that represent the corresponding desired output(s) of the plant to generate the control signal to be provided to the actuator. However, it may be desirable to replace the wired network used in prior feedback control systems with one or more wireless networks to, for example, reduce installation cost/complexity, enhance flexibility/mobility of the elements of the feedback control system, etc.

The replacement of wired networks with wireless networks may be relatively straightforward for controlled systems that have slow dynamics and can tolerate a large control time-constant, and/or can have low reliability requirements. However, replacement of wired networks with wireless networks for controlled systems that have fast dynamics and thus require a small control time-constant, and/or have high reliability requirements, is more challenging because, for example, a wireless network can introduce time delays or, in other words, latency in the sensing and/or actuation of the feedback control system. Such time delays (or latencies) can result in performance degradation, or even instability, in the feedback control system.

A graph **100** illustrating example latency and reliability requirements for different types of industrial systems to be controlled by a feedback control system is provided in FIG. **1**. The graph **100** of FIG. **1** illustrates three (3) example classes of controlled systems, labelled Class A (also corresponding to reference numeral **105**), Class B (also corresponding to reference numeral **110**) and Class C (also corresponding to reference numeral **115**), with different latency and reliability requirements. Class A represents a first class of controlled systems that have slow dynamics (e.g., high time-constant) and can tolerate low reliability, which include systems such as maintenance systems **120**, diagnostic systems **125**, etc. Class B represents a second class of controlled systems that have faster dynamics (e.g., lower time-constant) than the Class A systems, and require higher reliability than the Class A systems, which include systems such as machine tools **130**, production lines **135**, storage and logistics systems **140**, industrial robots **145**, etc. Class C represents a third class of controlled systems that have high dynamics (e.g., low time-constant) and require high reliability, which include systems such as industrial presses **150**, packaging machines **155**, printing machines **160**, etc.

Prior techniques for migrating feedback control systems, such as those in the areas of industrial automation and manufacturing, focus on the Class A controlled systems described above, which can tolerate high latency (e.g., are characterized by slow dynamics/high time-constant) and low reliability. However, such techniques typically cannot meet the low latency requirements of the Class B and C controlled systems described above, and/or other latency-sensitive and reliability-sensitive controlled systems, such as remote-controlled drones, etc. Prior attempts to migrate feedback control systems for such latency-sensitive and/or reliability-sensitive controlled systems to wireless networks focus on reducing the latency and improving the reliability of the wireless networks, but such attempts may still be insufficient to meet the latency and/or reliability requirements of the Class B and C controlled systems described above, as well as other controlled systems that are latency-sensitive and/or reliability-sensitive.

Unlike such prior feedback control techniques, example predictive feedback control solutions disclosed herein enable use of wireless networks to perform feedback control of the Class B and C controlled systems described above, as well as other controlled systems that are latency-sensitive and/or reliability-sensitive. Such example predictive feedback control solutions disclosed herein can be implemented with any existing or future wireless time sensitive network (WSTN), such as a WSTN conforming to the Institute of Electrical and Electronics Engineers (IEEE) 802.11ax standard, that provides time synchronization between wireless devices communicating in the WSTN. As described in further detail below, such time synchronization can be provided by timestamps included with transmitted messages, a synchronized real time clock (RTC) source provided by the WSTN, etc.

As disclosed in further detail below, some example predictive feedback control solutions implemented in accordance with the teachings of this disclosure include an example state prediction neural network to prevent performance degradation when a wireless network, which typically has larger latency than a wired network, is used instead of, or is used to replace, a wired network in the feedback control system. As disclosed in further detail below, the state prediction neural network utilizes information provided by the wireless devices communicating in the WSTN, such as network timing synchronization, timestamping services, a known maximum latency of the WTSN (e.g., at least known with a target level of reliability), etc., to process the reported output measurements of the controlled system, which may exhibit delay/latency due to the wireless network, to predict a future state of the controlled system, which can be applied to the controller that is to generate the control signal for use by the actuator that is to adjust operation of the controlled system. In some such examples, the state prediction neural network enables use of the same (or similar) controller that would be used with a wired network implementation.

A block diagram of an example predictive wireless feedback control system **200** implemented in accordance with teachings of this disclosure is illustrated in FIG. **2**. The wireless feedback control system **200** of the illustrated example is divided into an example target side **205** and an example control side **210**. The target side **205** of the predictive wireless feedback control system **200** includes an example target system **215** to be controlled, which is also referred to herein as an example controlled system **215** or an example plant **215**. The target system **215** (or controlled system **215** or plant **215**) can correspond to any type(s) and/or number(s) of systems capable of being controlled by a feedback control system. For example, the target system **215** (or controlled system **215** or plant **215**) can correspond to one of more of the example systems illustrated in FIG. **2**, machinery operating in a factory (e.g., a conveyor belt, drill, press, robot, oven, assembly line, etc.), one or more remote controlled drones, an autonomous vehicle (e.g., a self-driving car), one or more navigation/driving systems of a vehicle (e.g., autonomous parking system, a cruise control system, a lane control system, etc.), etc.

The target system **215** of the illustrated example also includes an example actuator **220** and one or more example sensors **225**. The actuator **220** of the illustrated example can correspond to any type(s) and/or number(s) of actuators capable of adjusting one or more inputs of the target system **215**. For example, the actuator **220** can include one or more servos, pumps, relays, valves, motors, switches, power supplies, nozzles, injectors, ports, restrictors, etc., to adjust one or more of the inputs of the target system **215**. The sensor(s) **225** of the illustrated example can correspond to any type(s) and/or number(s) of sensor(s) capable of measuring one or more outputs of the target system **215**. For example, the sensor(s) **225** can include one or more voltage sensors, current sensors, optical sensors, position sensors, pressure sensors, thermal sensors, accelerometers, velocity sensors, etc.

The control side **210** of the predictive wireless feedback control system **200** includes an example predictive feedback control solution **230**, which includes an example controller **235**, and an example state prediction neural network **240**. The controller **235** of the illustrated example can correspond to any type(s) and/or number(s) of controller(s) capable of generating control signal(s) to be provided to the actuator **220**. In some examples, the controller **235** is implemented by a logic circuit that performs a conventional proportional control algorithm, a conventional integral control algorithm, a conventional derivative control algorithm, or any combination thereof. In some examples, the controller **235** implements a nonlinear PID control algorithm as disclosed in U.S. patent application Ser. No. 16/455452 (Attorney Docket No. AB5991-US), titled "PREDICTIVE WIRELESS FEEDBACK CONTROL LOOPS," which was filed on the same date as the instant patent application and is incorporated herein by reference.

The state prediction neural network **240** of the illustrated example operates to implement predictive feedback control in accordance with the teachings of this disclosure. In some examples, the state prediction neural network **240** is implemented as a model in software, such as in a distributable binary executable by a computing system, such as the example processor platform **1600** of FIG. **16**. In some examples, the state prediction neural network **240** is a neural network model implemented in software as a distributable binary executable by special purpose hardware, such as neuromorphic hardware, one or more artificial intelligence (AI) accelerator chips, one or more Intel® and/or Intel® Movidius™ neural compute sticks, etc., or any combination thereof. Further details concerning the state prediction neural network **240** are provided below. Although the state prediction neural network **240** is depicted as a neural network in the illustrated example, in other examples, other machine learning techniques could be used to perform the functions of the state prediction neural network **240** in the predictive wireless feedback control system **200**.

In the illustrated example of FIG. **2**, wireless aspects of the predictive wireless feedback control system **200** are implemented by an example control-side receiver **250**, an example control-side transmitter **252**, an example target-side receiver **254** and an example target-side transmitter **256**. The target-side transmitter **256** and the control-side receiver **250** of the illustrated example communicate via an example WTSN **260** to implement an example wireless sensing link (WSL) **262**. Likewise, the control-side transmitter **252** and the target-side receiver **254** of the illustrated example communicate via the WTSN **260** to implement an example wireless actuation link (WAL) **264**. For example, the WSL **262** can correspond to any protocol defining message formats, message timing, etc., by which the target-side transmitter **256** transmits example sensor messages **266** to the control-side receiver **250**. As such, the control-side receiver

250 is an example of means for receiving measurements of the target system **215** via the WSL **262**. In the illustrated example, an example sensor message **266** includes an example data payload **268** and an example transmit timestamp **270**. The example data payload **268** includes sampled values of measurement(s) taken by the sensor(s) **225**, and the transmit timestamp **270** is a timestamp representing the time at which the target-side transmitter **256** transmitted the sensor message **266**. Likewise, the WAL **264** can correspond to any protocol defining message formats, message timing, etc., by which the control-side transmitter **252** transmits example actuation messages **272** to the target-side receiver **254**. As such, the control-side transmitter **252** is an example of means for transmitting values of a control signal to the target system **215** via the WAL **264**. In the illustrated example, an example actuation message **272** includes an example data payload **274** and an example transmit timestamp **276**. The example data payload **274** includes sampled values of control signal(s) generated by the controller **235**, and the transmit timestamp **276** is a timestamp representing the time at which the control-side transmitter **252** transmitted the actuation message **272**.

The WTSN **260** of the illustrated example can correspond to any number(s) and/or types(s) of WSTNs capable of (i) ensuring time synchronization among the control-side receiver **250**, the control-side transmitter **252**, the target-side receiver **254** and the target-side transmitter **256**, and (ii) meeting a target, maximum expected communication latency (e.g., in terms of seconds, milliseconds, microseconds, etc.) with a target level of reliability (e.g., in terms of a percentage, such as 99%, 95% etc.). For example, such time synchronization and maximum expected communication latency requirements can be met by the IEEE 802.1AS synchronization feature enabled by the IEEE 802.11 timing measurement capability of an IEEE 802.11ax network. In such examples, the control-side receiver **250**, the control-side transmitter **252**, the target-side receiver **254** and the target-side transmitter **256** include respective, example medium access control (MAC) synchronizers **278**, **279**, **280** and **281** to implement WSTN synchronization, such as the IEEE 802.1AS synchronization feature of an IEEE 802.11ax network

As disclosed in further detail below, the example state prediction neural network **240** is trained to use measurement values of the target system **215** received in the sensor messages **266** to predict a future state of the target system **215**. For example, the state prediction neural network **240** accounts for the communication latencies exhibited by the wireless feedback control system **200** to predict a future state of the target system **215** that can be applied to the controller **235** to cause the controller **235** to generate an appropriate control signal corresponding to what the state of the target system **215** is expected to be at the time the control signal ultimately reaches the target system **215** (e.g., reaches the actuator **220**). In some examples, the communication latencies exhibited by the wireless feedback include a sensing link latency, τ_s, associated with the communication of the sensor messages **266**, which carry the measurement values of the target system **215**, over the WSL **262** implemented over the WSTN **260**. The sensing link latency, τ_s, of the WSL **262**, may be random. In some examples, there is also an actuation link latency, τ_a, associated with the communication of the actuation messages **272** over the WAL **264** implemented over the WSTN **260**. In such examples, to enable the controller **235** to apply the appropriate correction action, the state prediction neural network **240** accepts as include a received measurement corresponding to a prior time $t-\tau_s$, where τ_s is the random sensing link latency, and predicts the target system state in the future by a prediction time interval corresponding to $\tau_s+\tau_a$ relative to the time associated with the received measurement, where τ_a is the actuation link latency. As disclosed in further detail below, the state prediction neural network **240** uses the received measurements of the target system **215** and a history of control signal values sent to the target system **215** (e.g., to the actuator **220**), to predict what the actual state of the target system **215** will be at the moment the actuator **220** is to apply an actuation based on the control signal that is currently being generated by the controller **235**.

In this way, the state prediction neural network **240** overcomes delays in the messages **266** and **272** being communicated wirelessly in the wireless feedback control system **200**. In the illustrated example, the state prediction neural network **240** is located logically between the control-side receiver **250** and the controller **235**. In some examples, the state prediction neural network **240** is integrated with the controller **235**, for example, as one or more software processes implemented on the same processor (e.g., central processing unit—CPU) implementing the controller **235**, as one or more software and/or firmware processes implemented on the same digital signal processor (DSP) implementing the controller **235**, as one or more firmware processes implemented by a microcontroller (e.g., microcontroller unit—MCU) implementing the controller **235**, etc. In some examples, the state prediction neural network **240** is implemented in a device that is separate from the controller **235**. In some examples, the state prediction neural network **240** is implemented as part of the MAC layer in one or more of the wireless transceivers included in the control side of the wireless feedback control system **200**. For example, the state prediction neural network **240** could be implemented by the control-side receiver **250**, the control-side transmitter **252**, the target-side receiver **254** and/or the target-side transmitter **256**, such as in one or more of the MAC synchronizers **278**, **279**, **280** and/or **281** included in the control-side receiver **250**, the control-side transmitter **252**, the target-side receiver **254** and/or the target-side transmitter **256**.

In the illustrated example, the wireless feedback control system **200** determines the wireless communication latencies and, in some examples, determines when to apply control signal values to the actuator **220**, based on the timestamps **270** and **276** included in the messages **266** and **272**. As such, the target-side transmitter **256** includes an example transmit timestamper **282** to timestamp the sensor messages **266** with the timestamps **270**, which indicate the respective times at which the measurements contained in the data payloads **268** of the respective sensor messages **266** were transmitted. The control-side receiver **250** includes an example sensing link latency determiner **284** to determine the sensing link latency, τ_s, of the WSL **262** based on the transmit timestamp **270** included in a given sensor message **266** and a receive time corresponding to a time at which the control-side receiver **250** received that sensor message **266**. For example, the sensing link latency determiner **284** may determine the sensing link latency, τ_s, of the WSL **262** as the difference between the receive time at which the control-side receiver **250** received that sensor message **266** and the transmit timestamp **270** included in the sensor message **266**. As disclosed above and in further detail below, the state prediction neural network **240** uses the calculated sensing link latency, τ_s, to predict a future state of the target system

215 relative to a prior time (e.g., $t-\tau_s$) associated with the measurement included in a given sensor message **266** being processed.

Similarly, in some examples, the client-side transmitter **252** includes an example transmit timestamper **286** to timestamp the actuation messages **272** with the timestamps **276**, which indicate the respective times at which the control signal values contained in the data payloads **274** of the respective actuation messages **272** were transmitted. The target-side receiver **254** includes an example actuation link latency determiner **288** to determine the actuation link latency, τ_a, of the WAL **264** based on the transmit timestamp **276** included in a given actuation message **272** and a receive time corresponding to a time at which the target-side receiver **254** received that actuation message **272**. For example, the actuation link latency determiner **288** may determine the actuation link latency, τ_a, of the WAL **264** as the difference between the receive time at which the target-side receiver **254** received that actuation message **272** and the transmit timestamp **276** included in the actuation message **272**. In the illustrated, the target-side receiver **254** includes an example actuation link latency reporter **296** to report the calculated actuation link latency, τ_a, to the control side **210** of the predictive wireless feedback control system **200** via a return path (e.g., channel, link, etc.) of the WAL **264**. In the illustrated example, the control-side transmitter **252** includes an example actuation link delay selector **290** to receive the actuation link latency, τ_a, reported by the actuation link latency reporter **296** via the WAL **264**. In the illustrated example, the actuation link latency reporter **296** provides the actuation link latency, τ_a, to the state prediction neural network **240**. As disclosed above and in further detail below, the state prediction neural network **240** uses the calculated actuation link latency, τ_a, to predict a future state of the target system **215** that is ahead of the prior time (e.g., $t-\tau_s$) associated with the measurement being processed by a prediction time interval corresponding to $\tau_s+\tau_a$. In some examples, the actuator **220** also uses the calculated actuation link latency, τ_a, to determine when to use the control signal value received in the given actuation message **272** to adjust the input(s) to the target system **215**.

In examples in which the target-side transmitter **256** does not include the transmit timestamper **282**, and/or the control-side transmitter **252** does not include transmit timestamper **286**, a synchronized real-time clock (RTC) can be provided to the target side **205** and/or the example control side **210** of the predictive wireless feedback control system **200** to enable determination of the communication link latencies.

It is noted that wireless feedback control loops with neural networks, as disclosed herein, are not limited to the architecture of the example wireless feedback control system **200** of FIG. **2**. Rather, in some examples, some or all of the functionality disclosed above as implemented by the example predictive feedback control solution **230**, the example controller **235**, the example state prediction neural network **240**, the example MAC synchronizers **278**, **279**, **280** and/or **281**, the example transmit timestamper **282**, the example sensing link latency determiner **284**, the example transmit timestamper **286**, the example actuation link latency determiner **288**, the example actuation link delay selector **290** and/or the example actuation link latency reporter **296** could be redistributed among different elements of the target side **205** and/or the control side **210** of the predictive wireless feedback control system **200**. For example, some or all of the functionality disclosed above as implemented by the example predictive feedback control solution **230**, the example controller **235**, the example state prediction neural network **240**, the example MAC synchronizers **278**, **279**, **280** and/or **281**, the example transmit timestamper **282**, the example sensing link latency determiner **284**, the example transmit timestamper **286**, the example actuation link latency determiner **288**, the example actuation link delay selector **290** and/or the example actuation link latency reporter **296** could be implemented as part of the target system **215** to be controlled, such as in one or more drivers provided to control the target system **215**. By way of example, if the target system **215** includes a motor, some or all of the functionality disclosed above as implemented by the example predictive feedback control solution **230**, the example controller **235**, the example state prediction neural network **240**, the example MAC synchronizers **278**, **279**, **280** and/or **281**, the example transmit timestamper **282**, the example sensing link latency determiner **284**, the example transmit timestamper **286**, the example actuation link latency determiner **288**, the example actuation link delay selector **290** and/or the example actuation link latency reporter **296** could be integrated into a driver provided for that motor to prevent, or reduce, performance degradation when using the motor in wireless networks.

FIG. **3** depicts an example simplified view **300** of the wireless feedback control system **200** to further illustrate the communication link latencies which the state prediction neural network **240** operates to overcome. The simplified view **300** of FIG. **3** includes the target system **215**, the actuator **220**, the sensor(s) **225**, the predictive feedback control solution **230** (which includes the controller **235** and the state prediction neural network **240**), the control-side receiver **250**, the control-side transmitter **252** and the WTSN **260** (which implements the WSL **262** and the WAL **264**). The simplified view **300** illustrates the two primary latencies exhibited by the wireless feedback control system **200**. The sensing link latency, τ_s, of the WSL **262** causes measurements of state of the target system **215** received by the control-side receiver **250** to be out-of-date. Thus, prior solution that computes a control signal based on such out-of-date information may not be appropriate when such control is actually applied to the actuator **220**. There is also the actuation link latency, τ_a, of the WAL **264**, which further delays when a control signal is received by the actuator **220**. For example, suppose that the sensing link latency τ_s and the actuation link latency τ_a are each equal to 25 ms. In such an example, the total system delay would be 50 ms. This means that for a set of sensed measurements, the corresponding control signal generated from such measurement will arrive at the actuator **220** approximately 50 ms after the measurements were sensed (with a possible additional delay Δc corresponding to the processing time of the predictive feedback control solution **230**, which is may be negligible relative to the sensing link latency τ_s and the actuation link latency τ_a). However, the configuration of the target system **215** may be different from what it was 50 ms ago and, thus, a control signal computed by a prior solution may not work as intended, thereby causing an undesired behavior of the target system **215**.

However, unlike prior control system solutions, the wireless feedback control system **200** includes several features to overcome the sensing link latency τ_s and the actuation link latency τ_a in the system. For example, to reduce the uncertainty and non-stationarity of the WSL **264** and the WAL **262**, improves the accuracy for the neural network **240**, the WTSN **260** (e.g. based on the IEEE 802.11ax protocol) is used as the wireless transport. To improve robustness to the sensing link latency, τ_s, of the WSL **262**, time-stamping is added to the sensor messages **266** to indicate how outdated each received measurement is. To improve robustness to the actuation link latency, τ_a, of the WAL **264**, the state prediction neural network **240** (implemented with, for example, a recurrent neural network (RNN), e.g. an long short-term memory (LSTM) neural network, etc.), is trained to input a sensed measurement that is delayed by the WSL **262** (e.g., with the delay known from the time-stamping), and predict what the state of the target system **215** will be at the moment when the control signal is transmitted via the WAL **264** and applied to the actuator **220**. In some examples, only partial information of the state of the target system **215** is measurable. In some such examples, the state prediction neural network **240** is also structured to predict the unmeasured complete state of the target system **215**, which is used to drive prediction of the future state of the target system **215**.

The controller **235** uses this predicted future value of the state of the target system **215** to calculate the correct control signal to be applied at this future time. The control signal is transmitted by the control-side transmitter **252** via the WAL **264** to the actuator **220**. When this control signal is applied by the actuator **220**, the state of the target system **215** will coincide with (e.g., match or be similar to) the future state predicted by the state prediction neural network **240** and, thus, the wireless control loop is expected to perform similarly to a wired control loop.

As disclosed in further detail below, the state prediction neural network **240** is trained offline based on information extracted from a wired control system using, for example, a back propagation procedure based on a prediction error. In some examples, the state prediction neural network **240** is further refined using reinforcement learning based on the control performance (e.g., tracking error) measured while the wireless feedback control system **200** is online. In some examples, the state prediction neural network **240** may provide a measure of the uncertainty of the predicted future state of the target system **215**. For example, uncertainty may increase for state predictions further into the future, uncertainty may increase when Signal-to-noise-ratio (SNR) decreases, etc. To provide this uncertainty, one disclosed example approach uses Bayesian neural networks to implement the state prediction neural network **240** such that the weights of the neurons of the neural network are distributions instead of deterministic values. Another disclosed example approach involves training the state prediction neural network **240** to output the mean and covariance (and/or other statistical characteristic(s)) of the predicted future state of the target system **215**. In some examples, the uncertainty information output from the state prediction neural network **240** is provided to the controller **235** to tune the control signal accordingly. For example, as uncertainty increases, the aggressiveness of the controller **235** may be reduced to maintain a smooth trajectory of the target system **215**.

In some disclosed examples, the predictive feedback control solution **230** of the wireless feedback control system **200** is structured to compute control signals for multiple, possible time moments. For example, such possible time moments can be based on the average actuation link latency, τ_a, of the WAL **264**, the maximum actuation link latency, τ_a, of the WAL **262**. In some examples, decision logic in the actuator **220** selects the control signal to apply in accordance of the observed actuation link latency, τ_a. In some such examples, at each sense-actuation cycle, the estimated probability distribution of actuation link latency, τ_a, of the WAL **262** delay updated.

An example operation **400** of the predictive wireless feedback control system **200** of FIG. **2** is illustrated in FIG. **4**. In the illustrated example operation **400** of FIG. **4**, example measurements **405** of the output of the target system **215** are sensed (e.g., by the sensor(s) **225**). The measurements **405** are represented by the signal x(t) in FIG. **4**. The target-side transmitter **256** samples (digitizes) the measurements **405**, encapsulates the sampled measurements **405** in the data payloads **268** of the sensor messages **266** along with the transmit timestamps **270**, and transmits the messages **266** via the WSL **262** to the control-side receiver **250**. The delivery of the sensor messages **266** over the WSL **262** exhibits a random delay τ_s (which may be caused by one or more factors, such as packet-errors over the wireless channel, non-deterministic access to the wireless channel, etc.).

When a sensor message **266** is received at the control side by the control-side receiver **250**, the sensing link latency determiner **284** determines the sensing link latency, τ_s, of the WSL **262** as the difference between the receive time at which the control-side receiver **250** received that sensor message **266** and the transmit timestamp **270** included in the sensor message **266**. As shown in FIG. **4**, the received measurement **410** is delayed relative to its sensed version **405** by the sensing link latency τ_s. The control-side receiver **250** provides the received measurement **310** to the state prediction neural network **240**.

In the illustrated example, a random actuation link delay, τ_a, is also exhibited on the WAL **264** for the actuation messages **272** sent by the control-side transmitter **252** to the target-side receiver **254**. To compensate for the delays introduced by the WSL **262** and the WAL **264**, the, the state prediction neural network **240** is used to forecast, as disclosed in further detail below, the future state **415** of the target system **215** at a prediction time interval $\tau_s+\tau_a$ in the future relative to the prior time associated with the received measurement being processed, which as noted above is delayed in time by the sensing link latency τ_s. As such, the prediction time interval represents a sum of the sensing link latency τ_s and the actuation link delay, τ_a. However, because the delay, τ_a, associated with delivery of the actuation messages **272** over the WAL **264** is random, the actuation link delay τ_a to be faced by the control signal currently being generated by the controller **235** is not known in advance. Several examples schemes to characterize the actuation link delay τ_a are disclosed herein.

In a first example estimation scheme, the actuation link delay τ_a is set to be the maximum expected latency $\tau_{a,MAX}$ for the WAL **264**. In some examples, the maximum expected latency for the WAL **264**, $\tau_{a,MAX}$, may be a configuration parameter that is known or determinable based on characteristics of the WTSN **260** over which the WAL **264** is implemented.

In a second example estimation scheme, the actuation link delay τ_a is considered to be a set of statistical values $\tau_{a,MAX}$, $\tau_{a,MIN}$, $\tau_{a,AVE}$, which represent the maximum expected latency $\tau_{a,MAX}$ for the WAL **264**, the minimum expected latency $\tau_{a,MAX}$ for the WAL **264**, and the average maximum expected latency $\tau_{a,AVE}$ for the WAL **264**, respectively. In some such examples, the set of statistical values for the actuation link latency are calculated and updated continually. Additionally or alternatively, in some examples, other statistical values, such as the modes of the latency distribution, are used to characterize the actuation link delay τ_a.

In a third example estimation scheme, the actuation link delay τ_a is considered to be a set of probabilistic values $\tau_{a,PROB}$, $\tau_{a,\sigma+}$, $\tau_{a,\sigma-}$. In this example, $\tau_{a,PROB}$ represents the most likely actuation link delay based on a probability distribution modeled from measurements of the actuation link delay, and $\tau_{a,\sigma+}$ and $\tau_{a,\sigma-}$ represent upper and lower bounds based on (e.g., proportional to) the standard deviation of the probability distribution. In some such examples, probability distribution modeled of the actuation link delay is calculated and updated continually.

To enable the control side **210** of the predictive wireless feedback control system **200** to learn the values/statistics of the actuation link latency, τ_a, of the WAL **264**, the actuation link latency determiner **288** calculates the differences between the receive time sat which the target-side receiver **254** receives actuation messages **272** and the transmit timestamps **276** included in those actuation message **272**. The resulting calculated actuation link latencies, τ_a are reported by the actuation link latency reporter **296** back to the control side **210** through a return message in the WAL **264** (and/or via reporting message via the WSL **262**). In this way, at the control side **210**, the measurements of the actuation link latency are available and can be used to track the latency statistics of the WAL **264**.

In some examples, a wireless adapter implementing the WSTN **260** can provide early feedback concerning the reliability of the WAL **264** to the control side **210** of the predictive wireless feedback control system **200**. For example, this reliability information can be extracted from the WTSN schedule used in the wireless adapter to transmit messages via WAL **264**. For example, the WTSN schedule can be analyzed to determine the number of scheduled opportunities (and the time separation between them) for message transmission over the WAL **264**. In some examples, these scheduling opportunities are decided by the WTSN network central scheduler, and are known by the WTSN wireless adapters ahead of time. The number of scheduled transmission opportunities available for the WAL **264** is related to the reliability of the WAL **264** (e.g., more transmission opportunities translates to higher reliability, whereas fewer transmission opportunities translates to lower reliability), the set of possible delays suffered in the WAL **264** will correspond to the time offsets for each of the scheduled opportunities in the WTSN schedule.

In the illustrated example, the predicted future state **415** output from the state prediction neural network **240** is fed to the controller **235**, which calculates the control signal **420**, represented by u(t) in FIG. **4**. As shown in FIG. **4**, the predicted future state **415** and the corresponding control signal **420** are determined for a future time that corresponds to the prediction time interval $\tau_s+\tau_a$ ahead of the prior, delayed time associated with the measurement being used to update the neural network **240**. This is because the controller **235** calculates the control signal u(t) based on the future state **415**, which is predicted for a time $\tau_s+\tau_a$ in the future relative to the prior, delayed time associated with the measurement, which is delayed in time by the sensing link latency τ_s. In some examples in which multiple values of the actuation link delay τ_a are considered, such as the set of statistical values $\tau_{a,MAX}$, $\tau_{a,MIN}$, $\tau_{a,AVE}$, the set of probabilistic values $\tau_{a,PROB}$, $\tau_{a,\sigma+}$, $\tau_{a,\sigma-}$, etc., the state prediction neural network **240** predicts multiple future values of the state of the target system **215**, which correspond to the respective different actuation link delay. In such examples, the controller determines multiple control signals corresponding respectively to multiple values representing the actuation link delay. However, in some examples, the actuation link delay selector **290** selects one of the multiple values of the actuation link delay τ_a as a representative value (e.g., based one applying a recent report of the actuation link delay to a probabilistic model of the actuation link delay), and provided this selected actuation link delay to the neural network **240**, which predicts the future state of the target system **215** which corresponds to that selected actuation link delay.

The client-side transmitter **252** samples (digitizes) the control signal (or multiple control signals determined for different values of the actuation link delay τ_a), encapsulates the sampled control signal **425** in the data payloads **274** of the actuation messages **272** along with the transmit timestamps **276**, and transmits the actuation messages **272** via the WAL **264** to the target-side receiver **254**. The delivery of the actuation messages **272** over the WAL **264** exhibits a random delay τ_a (which may be caused by one or more factors, such as packet-errors over the wireless channel, non-deterministic access to the wireless channel, etc.) Because the control signal u(t) is calculated for a time $\tau_s+\tau_a$ in the future relative to the delayed measurement value that was used (indirectly) to generate the control signal, and the delayed measurement value was delayed in time by the sensing link latency τ_s, and the actuation messages **272** exhibit a random delay τ_a, the resulting control signal values received at the actuator **220** will be received close to when need to be acted on by the actuator **220**.

Once the sampled control signal **425** conveyed by the actuation messages **272** are received by the actuator **220**, they are acted on by the actuator **220** based on their timestamps **276**. In some examples, by knowing when the control signals were sent and received it is possible to know when they must be applied because the delay to be compensated by the state prediction neural network **240** is known by design. For example, the actuation link latency determiner **288** can determine the random actuation link delay τ_a based on the difference between the received time the actuation messages **272** and transmit timestamps associated with those actuation messages **272**, and then determine the timing offset at which the sampled control signal **425** is to be acted on based on the difference. In examples in which multiple control signals that correspond to different values of the actuation link delay τ_a are received (e.g., corresponding to the set of statistical values $\tau_{a,MAX}$, $\tau_{a,MIN}$, $\tau_{a,AVE}$, the set of probabilistic values $\tau_{a,PROB}$, $\tau_{a,\sigma+}$, $\tau_{a,\sigma-}$, etc.), the actuation link latency determiner **288** selects the control signal associated with the value of the actuation link delay τ_a that is closest to the actuation link delay τ_a as the control signal to be provided to the actuator **220**. However, in some examples, instead of, or in addition to, timestamping the actuation messages **272** with the sending time, the actuation messages **272** may be time-stamped with the time for which the control signal is intended to be applied.

In the illustrated example of FIG. **4**, the actuator **220** transforms (e.g. with a zero order hold (ZOH) operation) the sampled control signal **425** to form a continuous time actuation signal **430**, which is fed to the target system **215**, thereby closing the predictive wireless feedback control loop.

A block diagram of an example data collection system **500** to collect training data to be used to train the example state prediction neural network **240** of FIGS. **2-4** is illustrated in FIG. **5**. The data collection system **500** of the illustrated example is a feedback control system that includes the target system **215**, the actuator **220**, the sensor(s) **225** and the controller **235** of the wireless feedback control system **200** (or suitable equivalents or similar versions of one or more of those elements). However, in contrast with the wireless feedback control system **200**, the data collection system **500** includes an example wired network **505** to communicate the measurements sensed by the sensor(s) **225** to the controller **235**, and to communicate the control signal generated by the controller **235** to the actuator **220** that controls the input(s) to the target system **215**. Thus, the data collection system **500** does not exhibit the communication latencies, such as the sensing link latency τ_s and the actuation link delay τ_a, exhibited by the wireless feedback control system **200**.

The data collection system **500** also includes an example data extraction monitor **510** to monitor the data collection system **500** and extract values of the state of the target system (represented by x(k) in FIG. **5**), values of the measurements sensed by the sensor(s) **225** for those values of the target systems states (represented by y(k) in FIG. **5**), and corresponding values of the control signal generated by the controller **235** and that resulted in those values of the target systems states (represented by u(k) in FIG. **5**). The target state values x(k), the corresponding measurement values y(k) and the corresponding control signal values u(k) collected by the data extraction monitor **510** represent the target (e.g., desired, ideal, etc.) operational performance for controlling the target system **215** to achieve a desired reference state corresponding to a reference signal **515** input to the controller **235**. As such, the data collected by the data extraction monitor **510** is stored as the training data to be used to train the state prediction neural network **240**. To yield robust training data, in some examples, the data collection system **500** is run multiple times using different reference signals **515** to excite the target system **215**.

In some examples, the data collection system **500** also includes an example noise generator **520** to add noise to the control signal values u(k) applied to the actuator **220**. In such example, to yield robust training data, the data collection system **500** is run multiple times with the noise generator **520** configured to generate noise at different power levels across at least some of the runs. By performing multiple system runs with different reference signals **515** and/or noise powers generated by the noise generator **520**, the collected training data is able to more fully characterize operation of the target system **215**, the actuator **220**, the sensor(s) **225** and the controller **235** in a wired control system, such as the data collection system **500**.

FIG. **6** illustrates an example training procedure **600** that may be used to train the example state prediction neural network **240** of FIGS. **2**-**4** using the training data collected by the example data collection system of FIG. **5**. In some examples, the state prediction neural network **240** is implemented with an RNN, and LSTM, etc. Another example implementation of the state prediction neural network **240** is illustrated in FIG. **8**, which is described in further detail below. In the illustrated example of FIG. **6**, the state prediction neural network **240** is trained based on the training data to a predict future value of the state of the target system **215** (represented by $\hat{x}(k)$ in FIG. **6**) for a future time that is a prediction time interval ahead of a time associated with a current measurement value being processed (represented by y(k) in FIG. **6**). As described above, the state prediction neural network **240** predicts the future value of the target system state based on the current measurement value y(k) and the sequence of control signal values (represented by u(k) in FIG. **6**) that were generated to control the target system **215** during the prediction time interval between the time associated with the current measurement y(k) and the future time corresponding to the predicted future value of the target system state.

As described above, in some examples, the prediction time interval corresponds to the sum of the sum of the sensing link latency τ_s and the actuation link delay τ_a, that is, $\tau_s+\tau_a$. The example state prediction neural network **240** of FIGS. **2**-**4** is structured to operate on discrete time data. Therefore, in the training procedure **600** of FIG. **6**, and during operation as described above and in further detail below, the prediction time interval is divided (e.g., sampled) into a number of sample times (represented by τ in FIG. **6**) that corresponds to a data sampling rate employed in the system **200**. In other words, in the illustrated examples disclosed herein, τ represents that number of sample times that corresponds to the prediction time interval (e.g., $\tau_s+\tau_a$).

With the foregoing in mind, the state prediction neural network **240** is trained iteratively for a given prediction time interval τ according to the example training procedure **600** as follows. At each processing iteration, the state prediction neural network **240** is trained based on next measurement value y(k) taken from the training data. That next measurement value y(k) represents a delayed measurement that would be received by the state prediction neural network **240** in the system **200** with a sensing link latency τ_s. As described above, the future state of the target system **215** predicted by the state prediction neural network **240** corresponds to a future time that is the prediction time interval ahead of the timer associated with the measurement, which corresponds to τ time samples ahead of the measurement value y(k). In other words, a goal of the training procedure **600** is to train the state prediction neural network **240** to predict the future value $\hat{x}(k+\tau)$ of the target system state relative to the input measurement y(k).

Accordingly, at each processing iteration, an example training data set **605** is constructed from the training data collected by the data collection system **500** as follows. The training data set **605** for the given processing iteration is constructed to include, from the collected training data, the next measurement value y(k) to be processed, as well as the sequence of control values [u(k), u(k+1), . . . , u(k+τ)], which represent the sequence of control signal values that were generated to control the target system **215** during the prediction time interval from the time associated with the measurement (k) to the future time (k+τ) for which the state of the target system **215** is to be predicted. The next measurement value y(k) and the sequence of control values [u(k), u(k+1), . . . , u(k+τ)] form the training inputs to the neural network **240**. The training data set **605** for the given processing iteration is also constructed to include, from the collected training data, the sequence of measured states [x(k), x(k+1), . . . , x(k+τ)] of the target system **215**. The sequence of measured states [x(k), x(k+1), . . . , x(k+τ)] corresponds to the actual target system states resulting from the corresponding sequence of control values [u(k), u(k+1), . . . , u(k+τ)]. As described above, the neural network **240** is also designed to predict the complete state of the target system **215** from the measurements. Accordingly, the training data set **605** is also constructed to include, from the training data, the complete state x(k) of the target system **215** corresponding to the next measurement value y(k) to be processed. The target system state value x(k) also forms a training input to the neural network **240**.

Once the training data set **605** is formed, the neural network **240** is trained during a given training iteration as follows. The measurement value y(k) to be processed during this training iteration and the corresponding measured state value x(k) from the training data set **605** are input to the neural network **240**. Then, each one of the sequence of control values [u(k), u(k+1), . . . , u(k+τ)] is applied sequentially to the neural network **240**, which predicts a corresponding future value [$\hat{x}(k)$, $\hat{x}(k+1)$, . . . , $\hat{x}(k+\tau)$] for each one of the sequence of control values applied sequentially to the neural network **240**. For each predicted future state value $\hat{x}(k+i)$, an example error calculator **610** is used to calculate a prediction error, such as a mean squared error (MSE), between the predicted future state value $\hat{x}(k+i)$ and the corresponding measured state value x(k+i) in the training data set **605**. In the illustrated example, the resulting prediction error output from the error calculator **610** for a given predicted future state value $\hat{x}(k+i)$ operates as a loss function that is applied to a backpropagation algorithm that updates the neurons of the neural network **240**.

At the conclusion of applying the sequence of control values [u(k), u(k+1), . . . , u(k+τ)] to the neural network **240**, the final predicted future state value $\hat{x}(k+\tau)$ corresponds to the output predicted future state of the target system **215** for the future time that is predicted time interval ahead of the time (k) associated with the measurement value y(k) processed during that iteration. In the illustrated example, the training procedure **600** continues iterating through training sets constructed as described above for the next available measurement value y(k) until the prediction error output from the error calculator **610** satisfies (e.g., is less than, less than or equal to, etc.) a target performance threshold. In some examples, the training procedure **600** is then repeated for different possible values of the prediction time interval τ. For example, for each execution of the training procedure **600**, a value of the prediction time interval τ can be selected (e.g., randomly, sequentially, etc.) from a range of possible prediction time intervals τ that is determined based on latency characteristics of the WTSN **260** implementing the WSL **262** and the WAL **264**. In some such examples, the training procedure **600** is repeated until the neural network **240** is trained for a threshold number of different possible prediction time intervals τ.

An example implementation of the predictive feedback control solution **230** in the wireless feedback control system **200** is illustrated in FIG. **7**. In the example of FIG. **7**, the wireless feedback control system **200** includes the actuator **220**, the example sensor(s) **225**, the feedback control solution **230**, the example control-side receiver **250**, the example control-side transmitter **252**, the example target-side receiver **254** and the example target-side transmitter **256**, as described above. In the example of FIG. **7**, the predictive feedback control solution **230** includes the example controller **235** and the state prediction neural network **240**, as described above. However, as shown in the illustrated example, the predictive feedback control solution **230** also includes an example neural network updater **705** update (e.g., refine) the state prediction neural network **240** during operation in the wireless feedback control system **200**. As such, the neural network updater **705** is an example of means for updating the neural network **240**. However, other examples of means for updating the neural network **240** are disclosed in further detail below.

The neural network updater **705** includes an example time delayer **710**, an example reward policy enforcer **715** and an example error calculator **720**. The example training procedure **600** of FIG. **6** used a prediction error based on a difference between the predicted future state value $\hat{x}(k+i)$ and the corresponding measured state value x(k+i) in the training data set **605** as the cost function to update the neural network **240**. However, in the wireless feedback control system **200**, the measured state value x(k+i) is a for a time in the future and, thus, is not known when the neural network **240** predicts the future state value $\hat{x}(k+i)$. Thus, the example neural network updater **705** employs a different cost function to update the neural network **240**. In the illustrated example, the neural network updater **705** determines a cost function representative of a tracking performance error, which is fed into any appropriate backpropagation algorithm, such as the backpropagation algorithm **615** of FIG. **6**, to refine the neurons of the neural network **240** during operation in the wireless feedback control system **200**.

For example, the tracking performance error determined by the neural network updater **705** corresponds to a difference between the current measurement of the state of the target system **215** as reported to the neural network **240** (represented by $y(k-\tau_s)$ in FIG. **7**) and a correspondence reference value **725** representative of a desired target state (e.g., a reference state) of the target system **215** at the time corresponding to the current measurement. Because the current measurement of the state of the target system **215**, $y(k-\tau_s)$, is delayed by the sensing link latency τ_s, the neural network updater **705** includes the example time delayer **710** to also delay the reference value **725** by the currently measured sensing link latency τ_s (e.g., by a number of time samples corresponding to the sensing link latency τ_s). The neural network updater **705** includes the error calculator **720**, which may implement a similar or different error calculation as the error calculator **610** of FIG. **6**, to determine the tracking performance error based on the current measurement of the state of the target system **215**, $y(k-\tau_s)$, and the delayed reference value **725** output from the time delayer **710**.

In some examples, the neural network updater **705** includes the reward policy enforcer **715** to apply a reward policy to the tracking performance error calculated by the error calculator **720** before the error is used (e.g., by a backpropagation algorithm) to update the neural network **240**. Example reward policies that could be applied to the tracking performance error include, but are not limited to, a Monte-Carlo reward policy, and actor-critic reward policy, etc. However, in some examples, the reward policy enforcer **715** is omitted and the tracking performance error calculated by the error calculator **720** is processed by the backpropagation algorithm to update the neural network **240** during operation in the wireless feedback control system **200**.

An example implementation of the state prediction neural network **240** of FIGS. **2-4**, **6** and/or **7** is illustrated in FIG. **8**. The state prediction neural network **240** of FIG. **8** is an example of means for predicting a value of a state of the target system **215** at a future time relative to a prior time associated with a measurement of the target system **215** received via the WSL **262**. However, other examples of means for predicting such future values of the states of the target system **215** are disclosed in further detail below. The example neural network **240** of FIG. **8** is an RNN that includes two example neural networks **805** and **810**, which are examples of first neural network means and second neural network means, respectively. In the illustrated example, the neural networks **805** and **810** are each fully connected. In the illustrated example, the neural network **805** corresponds to an example observer neural network **805** that is trained (e.g., indirectly) to estimate of a full observed state of the target system **215** from a received measurement of the target system **215**. In the illustrated example, the neural network **810** corresponds to an example predictor neural network **810** trained to predict future values of the state of the target system **215** a prediction time interval ahead of the measurements values based on input measurement values and control signal values sent to the target system **215** for actuation during the prediction time interval. Thus, the input data applied to the state prediction neural network **240** of the illustrated example includes the delayed measurements y(k−τ) reported by the sensor(s) **225** via the

WSL **262** to the neural network **240**, and the sequence of control signal values (u(k−τ), u(k−τ+1), u(k−τ+2) . . . , u(k)) previously generated by the controller **235** for actuation by the actuator **220** during the prediction time interval or, in other words, the sequence of control signal values (u(k−τ), u(k−τ+1), u(k−τ+2) . . . , u(k)) sent by the controller **235** to the actuator **220** via the WAL **264** for the τ samples times between the prior time associated with the measurement value y(k−τ) being processed and the future time (k) for which the future state value of the targets system **215** is to be predicted.

(As noted above, the prediction time interval is divided (e.g., sampled) into a number of sample times τ that corresponds to a data sampling rate employed in the system **200**. In other words, in the illustrated examples disclosed herein, τ represents that number of sample times that corresponds to the prediction time interval, e.g., $\tau_s+\tau_a$. To simplify the notation, in FIG. **8**, the variable k represents the sample time corresponding the future time for which the neural network **240** is to predict the future state value of the target system **215** or, in other words, k represents the sample time corresponding to $t+\tau_a$, where t represents the current time. Because τ represents that number of sample times that corresponds to the prediction time interval, e.g., $\tau_s+\tau_a$, in FIG. **8**, the variable k−τ represents the sample time corresponding to the prior time of the measurement value y being processed, or in other words, k−τ represents the sample time corresponding to $t-\tau_s$, where t represents the current time.)

In the illustrated example of FIG. **8**, the observer neural network **805** accepts as input the received, delayed measurement value y(k−τ) and the first control signal value u(k−τ) in the sequence of control signal values, which corresponds to the control signal value that was previously generated by the controller **235** for application to the actuator **220** at the time of the received, delayed measurement value y(k−τ). In the example of FIG. **8**, the observer neural network **805** was trained (e.g., based on the example procedure **600** of FIG. **6**) to predict, from those inputs, the value of the state (e.g., the full observable state, also referred to as an extended state, which may include the measurement value as well as other unmeasured outputs) of the target system **215** one sample time after the sample time associated with the delayed measurement value y(k−τ) and the first control signal value u(k−τ), that is, the observer neural network **805** predicts x(k−τ+1).

In the illustrated example of FIG. **8**, the state prediction x(k−τ+1) output from the observer neural network **805** is fed as input to the predictor neural network **810**. The predictor neural network **810** also accepts as input the remaining control signal values in the sequence of control signal values, that is, remaining ones of the sequence of control signal values (u(k−τ+1), u(k−τ+2) . . . , u(k)) described above. In the illustrated example, the predictor neural network **810** performs a sequence of processing iterations to process each of the remaining ones of the sequence of control signal values sequentially to predict a corresponding future value of the state of the target system **215** that is one sample time ahead of the sample time of control signal value applied to the predictor neural network **810** during that processing iteration. For example, the input to the predictor neural network **810** performs τ processing iterations, i=1, . . . , τ, where τ corresponds to the number of sample times in the prediction time interval. At the i^{th} processing iteration, the predictor neural network **810** uses the control signal value u(k−τ+i) determined by the controller **235** for actuation at that sample time to predict the value of the state of the target system **215** advanced one sample time ahead of the sample time of the control signal value, that is, $\hat{x}(k-\tau+i+1)$. This predicted state value is fed back to the predictor neural network **810** as shown in FIG. **8**, and at the next processing iteration, the next control signal value in the sequence is processed. Once the number of iterations, τ, corresponding to the number of sample times in the prediction time interval is completed, the resulting output of the predictor neural network **810** is the predicted future value of the state of the target system **215** that is advanced in time by the prediction time interval relative to the time of the received measurement initially processed by the neural network **240**. Thus, in the illustrated example, the predictor neural network **810** operates at a faster rate than the observer neural network **805** because the predictor neural network **810** performs τ processing iterations for each processing iteration performed by the observer neural network **805**.

As described above, the predicted future state values output from the neural network **240** is input to the controller **235** to generate the control signal. Because the controller **235** uses the predicted future state values from the neural network **240**, the controller **235** generates its control signal for a state of the target system **215** that has not happened yet, but is expected happen by the time the control signal arrives to the target system **215** wirelessly via the WAL **264**.

In some examples, the neural network **240** may also provide a measure of the uncertainty in the predictions of the future state values of the target system **215**. For example, predictions further in time may have greater uncertainty. Additionally or alternatively, the uncertainty may increase as SNR decreases. An example approaches to include such uncertainty is to implement the neural network **805** and/or **810** as Bayesian neural networks where instead of deterministic values for the neuron weights, there are distributions of weights for the neurons. Another example approach to include such uncertainty is to train the neural network **805** and/or **810** to output the mean and covariance of their predictions. The uncertainty information can be fed to the controller **235** to tune the control signal accordingly. For example, as uncertainty increases, the controller **235** may lower the aggressiveness of the control signal to maintain a smooth trajectory of the state of the target system **215**.

FIGS. **9-12** illustrate example operational results obtained by an example implementation of the neural network **240** in the example wireless feedback control system **200**. In the illustrated example of FIGS. **9-12**, the target system **215** is a triple integrator with dynamics given by Equation 1, which is:

$$\dot{x}_1=x_2$$

$$\dot{x}_2=x_3$$

$$\dot{x}_3=u \qquad \text{Equation 1}$$

In Equation 8, the state of the target system **215** is presented by (x_1, x_2, x_3), and u represents the control signal. The control signal is generated by the controller **235** according to the proportional control algorithm of Equation 2, which is:

$$u=-Ke+v \qquad \text{Equation 2}$$

In Equation 2, where K is a diagonal matrix with elements $k_{i,i}>0, i\in\mathbb{Z}\,[1,3]$, v a function depending on the reference and $e=[x_1-\text{ref}\ x_2-\dot{\text{ref}}\ x_3-\ddot{\text{ref}}]^T$. In the examples of FIGS. **9-12**, the reference is ref=A sin(ωt).

The tracking performed by the controller **235** in the absence of communication delays (e.g., when the system is wired) is shown in FIG. **9**. The line labeled **905** represents the performance (state) of the target system **215** and the line labeled **910** is the reference to be tracked. In the illustrated example, only output of the target system **215** corresponding to the state x_1 is shown.

FIG. **10** illustrates operation of the system with a delay of 50 ms without state prediction as disclosed herein. In FIG. **10**, the line labeled **1005** is the reference to be tracked, the line labeled **1010** is the performance (state) of the target system **215**, and the line labeled **1015** is the state delayed by 50 ms simulating the wireless network latency. In this illustrated example, the state corresponding to the line labeled **1015** is being fed to the controller **235**.

FIG. **11** illustrates operation of the system with a delay of 50 ms with state prediction as disclosed herein. The line labeled **1105** is the reference to be tracked, the line labeled **1110** is the performance (state) of the target system **215**, the line labeled **1115** is the target system state with 50 ms delay, which is fed to the controller **235**, and the line labeled **1120** is the output of the prediction neural network **240**. Thus, FIG. **11** illustrates operation of the prediction neural network **240**, but the controller **235** is still operating on the delayed (unpredicted) state of the target system **215**. As shown in FIG. **11**, the prediction neural network **240** foresees where the target system state will be 50 ms in the future, which is why the line labeled **1120** coincides in time with the line labeled **1010**. Note that, in this example, the prediction neural network **240** is fed with the three states $x=[x_1(t-50 \text{ ms})\ x_2(t-50 \text{ ms})\ x_3(t-50 \text{ ms})]^T$ and predicts the future for each one. For sake of simplicity, FIG. **11** illustrates just the prediction of x_1 which coincidently is the prediction that had the largest error.

FIG. **12** illustrates operation of the system with a delay of 50 ms with state prediction as disclosed herein. However, in this example, the predicted state that is output from the prediction neural network **240** is fed to the controller **235** instead of the delayed state of the target system **215**. As shown in FIG. **12**, the performance is improved, with the line labeled **1205** representing the reference, the line labeled **1210** representing the performance (state) of the target system **215**, and the line **1215** representing the predicted state that is output from the predictor. (The line labeled **1220** represents the target system state with 50 ms delay, for reference.) Although the transient response is different from the one shown in FIG. **9** (for the wired system), the steady-state responses of FIGS. **9** and **12** are substantially the same.

While example manners of implementing the predictive wireless feedback control system **200** are illustrated in FIGS. **2-8**, one or more of the elements, processes and/or devices illustrated in FIG. **2-8** may be combined, divided, re-arranged, omitted, eliminated and/or implemented in any other way. Further, the example actuator **220**, the example sensors **225**, the example predictive feedback control solution **230**, the example controller **235**, the example state prediction neural network **240**, the example control-side receiver **250**, the example control-side transmitter **252**, the example target-side receiver **254**, the example target-side transmitter **256**, the example MAC synchronizers **278**, **279**, **280** and/or **281**, the example transmit timestamper **282**, the example sensing link latency determiner **284**, the example transmit timestamper **286**, the example actuation link latency determiner **288**, the example actuation link delay selector **290**, the example actuation link latency reporter **296**, and/or, more generally, the example predictive wireless feedback control system **200** of FIGS. **2-8** may be implemented by hardware, software, firmware and/or any combination of hardware, software and/or firmware. Thus, for example, any of the example actuator **220**, the example sensors **225**, the example predictive feedback control solution **230**, the example controller **235**, the example state prediction neural network **240**, the example control-side receiver **250**, the example control-side transmitter **252**, the example target-side receiver **254**, the example target-side transmitter **256**, the example MAC synchronizers **278**, **279**, **280** and/or **281**, the example transmit timestamper **282**, the example sensing link latency determiner **284**, the example transmit timestamper **286**, the example actuation link latency determiner **288**, the example actuation link delay selector **290**, the example actuation link latency reporter **296**, and/or, more generally, the example predictive wireless feedback control system **200** could be implemented by one or more analog or digital circuit(s), logic circuits, programmable processor(s), programmable controller(s), graphics processing unit(s) (GPU(s)), digital signal processor(s) (DSP(s)), application specific integrated circuit(s) (ASIC(s)), programmable logic device(s) (PLD(s)), field programmable gate arrays (FPGAs) and/or field programmable logic device(s) (FPLD(s)). When reading any of the apparatus or system claims of this patent to cover a purely software and/or firmware implementation, at least one of the example predictive wireless feedback control system **200**, the example actuator **220**, the example sensors **225**, the example predictive feedback control solution **230**, the example controller **235**, the example state prediction neural network **240**, the example control-side receiver **250**, the example control-side transmitter **252**, the example target-side receiver **254**, the example target-side transmitter **256**, the example MAC synchronizers **278**, **279**, **280** and/or **281**, the example transmit timestamper **282**, the example sensing link latency determiner **284**, the example transmit timestamper **286**, the example actuation link latency determiner **288**, the example actuation link delay selector **290**, and/or the example actuation link latency reporter **296** is/are hereby expressly defined to include a non-transitory computer readable storage device or storage disk such as a memory, a digital versatile disk (DVD), a compact disk (CD), a Blu-ray disk, etc. including the software and/or firmware. Further still, the example predictive wireless feedback control system **200** of FIGS. **2-8** may include one or more elements, processes and/or devices in addition to, or instead of, those illustrated in FIGS. **2-8**, and/or may include more than one of any or all of the illustrated elements, processes and devices. As used herein, the phrase "in communication," including variations thereof, encompasses direct communication and/or indirect communication through one or more intermediary components, and does not require direct physical (e.g., wired) communication and/or constant communication, but rather additionally includes selective communication at periodic intervals, scheduled intervals, aperiodic intervals, and/or one-time events.

Flowcharts representative of example hardware logic, machine readable instructions, hardware implemented state machines, and/or any combination thereof for implementing the predictive wireless feedback control system **200** are shown in FIGS. **13-15**, respectively. In these examples, the machine readable instructions may be one or more executable programs or portion(s) of an executable program for execution by a computer processor, such as the processors **1612** and/or **1712** shown in the example processor platform **1600** and/or **1700** discussed below in connection with FIGS. **16** and/or **17**. The one or more programs, or portion(s) thereof, may be embodied in software stored on a non-transitory computer readable storage medium such as a CD-ROM, a floppy disk, a hard drive, a DVD, a Blu-ray disk™, or a memory associated with the processors **1612** and/or **1712**, but the entire program or programs and/or parts thereof could alternatively be executed by a device other than the processors **1612** and/or **1712**, and/or embodied in firmware or dedicated hardware. Further, although the example program(s) is(are) described with reference to the flowcharts illustrated in FIGS. **13-15**, many other methods of implementing the example predictive wireless feedback control system **200** may alternatively be used. For example, with reference to the flowcharts illustrated in FIGS. **13-15**, the order of execution of the blocks may be changed, and/or some of the blocks described may be changed, eliminated, combined and/or subdivided into multiple blocks. Additionally or alternatively, any or all of the blocks may be implemented by one or more hardware circuits (e.g., discrete and/or integrated analog and/or digital circuitry, an FPGA, an ASIC, a comparator, an operational-amplifier (op-amp), a logic circuit, etc.) structured to perform the corresponding operation without executing software or firmware.

The machine readable instructions described herein may be stored in one or more of a compressed format, an encrypted format, a fragmented format, a compiled format, an executable format, a packaged format, etc. Machine readable instructions as described herein may be stored as data (e.g., portions of instructions, code, representations of code, etc.) that may be utilized to create, manufacture, and/or produce machine executable instructions. For example, the machine readable instructions may be fragmented and stored on one or more storage devices and/or computing devices (e.g., servers). The machine readable instructions may require one or more of installation, modification, adaptation, updating, combining, supplementing, configuring, decryption, decompression, unpacking, distribution, reassignment, compilation, etc. in order to make them directly readable, interpretable, and/or executable by a computing device and/or other machine. For example, the machine readable instructions may be stored in multiple parts, which are individually compressed, encrypted, and stored on separate computing devices, wherein the parts when decrypted, decompressed, and combined form a set of executable instructions that implement a program such as that described herein.

In another example, the machine readable instructions may be stored in a state in which they may be read by a computer, but require addition of a library (e.g., a dynamic link library (DLL)), a software development kit (SDK), an application programming interface (API), etc. in order to execute the instructions on a particular computing device or other device. In another example, the machine readable instructions may need to be configured (e.g., settings stored, data input, network addresses recorded, etc.) before the machine readable instructions and/or the corresponding program(s) can be executed in whole or in part. Thus, the disclosed machine readable instructions and/or corresponding program(s) are intended to encompass such machine readable instructions and/or program(s) regardless of the particular format or state of the machine readable instructions and/or program(s) when stored or otherwise at rest or in transit.

The machine readable instructions described herein can be represented by any past, present, or future instruction language, scripting language, programming language, etc. For example, the machine readable instructions may be represented using any of the following languages: C, C++, Java, C#, Perl, Python, JavaScript, HyperText Markup Language (HTML), Structured Query Language (SQL), Swift, etc.

As mentioned above, the example processes of FIGS. **13-15** may be implemented using executable instructions (e.g., computer and/or machine readable instructions) stored on a non-transitory computer and/or machine readable medium such as a hard disk drive, a flash memory, a read-only memory, a compact disk, a digital versatile disk, a cache, a random-access memory and/or any other storage device or storage disk in which information is stored for any duration (e.g., for extended time periods, permanently, for brief instances, for temporarily buffering, and/or for caching of the information). As used herein, the term non-transitory computer readable medium is expressly defined to include any type of computer readable storage device and/or storage disk and to exclude propagating signals and to exclude transmission media. Also, as used herein, the terms "computer readable" and "machine readable" are considered equivalent unless indicated otherwise.

"Including" and "comprising" (and all forms and tenses thereof) are used herein to be open ended terms. Thus, whenever a claim employs any form of "include" or "comprise" (e.g., comprises, includes, comprising, including, having, etc.) as a preamble or within a claim recitation of any kind, it is to be understood that additional elements, terms, etc. may be present without falling outside the scope of the corresponding claim or recitation. As used herein, when the phrase "at least" is used as the transition term in, for example, a preamble of a claim, it is open-ended in the same manner as the term "comprising" and "including" are open ended. The term "and/or" when used, for example, in a form such as A, B, and/or C refers to any combination or subset of A, B, C such as (1) A alone, (2) B alone, (3) C alone, (4) A with B, (5) A with C, (6) B with C, and (7) A with B and with C. As used herein in the context of describing structures, components, items, objects and/or things, the phrase "at least one of A and B" is intended to refer to implementations including any of (1) at least one A, (2) at least one B, and (3) at least one A and at least one B. Similarly, as used herein in the context of describing structures, components, items, objects and/or things, the phrase "at least one of A or B" is intended to refer to implementations including any of (1) at least one A, (2) at least one B, and (3) at least one A and at least one B. As used herein in the context of describing the performance or execution of processes, instructions, actions, activities and/or steps, the phrase "at least one of A and B" is intended to refer to implementations including any of (1) at least one A, (2) at least one B, and (3) at least one A and at least one B. Similarly, as used herein in the context of describing the performance or execution of processes, instructions, actions, activities and/or steps, the phrase "at least one of A or B" is intended to refer to implementations including any of (1) at least one A, (2) at least one B, and (3) at least one A and at least one B.

As used herein, singular references (e.g., "a", "an", "first", "second", etc.) do not exclude a plurality. The term "a" or "an" entity, as used herein, refers to one or more of that entity. The terms "a" (or "an"), "one or more", and "at least one" can be used interchangeably herein. Furthermore, although individually listed, a plurality of means, elements or method actions may be implemented by, e.g., a single unit or processor. Additionally, although individual features may be included in different examples or claims, these may possibly be combined, and the inclusion in different examples or claims does not imply that a combination of features is not feasible and/or advantageous.

An example program **1300** that may be executed to implement the example predictive wireless feedback control system **200** of FIGS. **2-8** is represented by the flowchart shown in FIG. **13**. The example program **1300** implements both example control-side processing **1305** associated with the control side **210** of the predictive wireless feedback control system **200**, and example target-side processing **1310** associated with the target side **205** of the predictive wireless feedback control system **200**. With reference to the preceding figures and associated written descriptions, the example program **1300** begins execution at block **1315** at which the example state prediction neural network **240** obtains measurements of the target system **215** (e.g., as sensed by the example sensor(s) **225**) via the WSL **262** (e.g., received by the example control-side receiver **250** from the example target-side transmitter **256**), as described above. At block **1320**, the state prediction neural network **240** processes the received measurements and control signal values output from the example controller **235** to predict, as described above, a future values of the state of the target system **215**. As described above, the future state values are predicted ahead in time from the received measurements a prediction time interval corresponding to (e.g., the summation of) the sensing link latency τ_s.associated with the WSL **262**, and the actuation link latency $\tau_{a,MAX}$ associated with the WAL **264**. An example program for implementing the processing at block **1320** is described below in connection with FIG. **14**.

At block **1330**, the controller **235** determines control signal values based on the predicted future state of the target system **215** obtained at block **1125** and a desired reference state of the target system **215**, as described above. At block **1335**, the controller **235** transmits the control signal values via the WSL **262** (e.g., transmitted by the example control-side transmitter **252** to the example target-side receiver **254**) to the actuator **220**, as described above. At block **1340**, the actuator **220** receives the control signal values and, at block **1345**, the actuator **220** operates on the control signal values at the appropriate time, as described above. At block **1350**, the sensor(s) **225** determine new measurements of the target system **215** and transmit the measurement via the WSL **262** to the control side **210** of the wireless feedback control system **200**, as described above, thereby completing the wireless feedback control loop until processing is no longer to continue (block **1350**).

An example program **1320**P that may be executed to implement the processing at block **1320** of FIG. **13**, and/or the example state prediction neural network **240** of FIGS. **2**,-**4**, **6**, **7** and/or **8**, is represented by the flowchart shown in FIG. **14**. With reference to the preceding figures and associated written descriptions, the example program **1220**P begins execution at block **1405** at which the state prediction neural network **240** accesses a received measurement of the target system **215** (e.g., received via the WSL **264**), as described above. At block **1410**, the sensing link latency determiner **284** determines the sensing link latency, τ_s, of the WSL **262***m* as described above. At block **1415**, the actuation link delay selector **290** determines the actuation link latency, τ_a, of the WAL **264** (e.g., as reported by the actuation link latency reporter **296**). At block **1420**, the state prediction neural network **240** determines the prediction time interval based on (e.g., as a summation of) the sensing link latency, τ_s, obtained at block **1410** and the actuation link latency, τ_a, obtained at block **1415**, as described above.

At block **1425**, the state prediction neural network **240** accesses, as described above, a sequence of control signal values previously generated by the controller **235** to control the target system **215** during the prediction time interval beginning at the prior time associated with the received measurement accessed at block **1405**. At block **1430**, the observer neural network **805** of the state prediction neural network **240** executes to predict an initial value of the state of the target system **215** based on the received measurement and a first control signal value corresponding to the prior time of the received measurement, as described above. At block **1435**, the predictor neural network **810** of the state prediction neural network **240** executes to iterate over the remaining sample times in the prediction time interval. For example, for each iteration, at block **1440**, the predictor neural network **810** is executed to predict a next value of the state of the target system **215** for a next sample time relative to the prior iteration. As described above, the predictor neural network **810** predicts the next value of the target system state based on the predicted initial value of the target system **215** obtained at block **1430**, and a next control signal value in the sequence of control signal values obtained at block **1425**. When the processing iterations complete (block **1445**), control proceeds to block **1450** at which the predictor neural network **810** outputs the last predicted value of the target system state as the predicted future value of the state of the target system **215** for a future time that accounts for the sensing link latency, τ_s, and the actuation link latency, τ_a, as described above.

An example program **1500** that may be executed to train the example state prediction neural network **240** of FIGS. **2**,-**4**, **6**, **7** and/or **8** is represented by the flowchart shown in FIG. **15**. With reference to the preceding figures and associated written descriptions, the example program **1500** begins execution at block **1505** at which the example data collection system **500** is used to collect target system state values, target system measurements and control signal values during operation of the target system **1505** and the controller **235** in a wired network. At block **1510**, the collected data is stored as training data for the state prediction neural network **240**.

At block **1515**, the example training procedure **600** is performed repeatedly for different possible values of the prediction time interval τ (e.g., selected randomly, sequentially, etc., from a range of possible intervals), as described above. For example, at block **1520**, the training procedure **600** is performed, as described above, to train the neural network **240** to predict a future value of the state of the target system **215** corresponding to a selected prediction time interval τ. Once training is completed for all selected values of the prediction time interval τ (block **1525**), the training procedure **600** outputs the trained neural network parameters for use by the neural network in the wireless feedback control system **200**.

FIG. **16** is a block diagram of an example processor platform **1600** structured to execute the instructions of FIGS. **11**, **12** and/or **13** to implement control side processing in the example predictive wireless feedback control system **200** of FIGS. **2**-**5**. The processor platform **1600** can be, for example, a server, a personal computer, a workstation, a self-learning machine (e.g., a neural network), a mobile device (e.g., a cell phone, a smart phone, a tablet such as an iPad™), or any other type of computing device.

The processor platform **1600** of the illustrated example includes a processor **1612**. The processor **1612** of the illustrated example is hardware. For example, the processor **1612** can be implemented by one or more integrated circuits, logic circuits, microprocessors, GPUs, DSPs, or controllers from any desired family or manufacturer. The hardware processor **1612** may be a semiconductor based (e.g., silicon based) device. In this example, the processor **1612** implements the example predictive feedback control solution **230**, the example controller **235**, the example state prediction neural network **240**, the example control-side receiver **250**, the example control-side transmitter **252**, the example MAC synchronizers **278** and **279**, the example sensing link latency determiner **284**, the example transmit timestamper **286** and the example actuation link delay selector **290**.

The processor **1612** of the illustrated example includes a local memory **1613** (e.g., a cache). The processor **1612** of the illustrated example is in communication with a main memory including a volatile memory **1614** and a non-volatile memory **1616** via a link **1618**. The link **1618** may be implemented by a bus, one or more point-to-point connections, etc., or a combination thereof. The volatile memory **1614** may be implemented by Synchronous Dynamic Random Access Memory (SDRAM), Dynamic Random Access Memory (DRAM), RAMBUS® Dynamic Random Access Memory (RDRAM®) and/or any other type of random access memory device. The non-volatile memory **1616** may be implemented by flash memory and/or any other desired type of memory device. Access to the main memory **1614**, **1616** is controlled by a memory controller.

The processor platform **1600** of the illustrated example also includes an interface circuit **1620**. The interface circuit **1620** may be implemented by any type of interface standard, such as an Ethernet interface, a universal serial bus (USB), a Bluetooth® interface, a near field communication (NFC) interface, and/or a PCI express interface.

In the illustrated example, one or more input devices **1622** are connected to the interface circuit **1620**. The input device (s) **1622** permit(s) a user to enter data and/or commands into the processor **1612**. The input device(s) can be implemented by, for example, an audio sensor, a microphone, a camera (still or video), a keyboard, a button, a mouse, a touchscreen, a track-pad, a trackball, a trackbar (such as an isopoint), a voice recognition system and/or any other human-machine interface. Also, many systems, such as the processor platform **1600**, can allow the user to control the computer system and provide data to the computer using physical gestures, such as, but not limited to, hand or body movements, facial expressions, and face recognition.

One or more output devices **1624** are also connected to the interface circuit **1620** of the illustrated example. The output devices **1624** can be implemented, for example, by display devices (e.g., a light emitting diode (LED), an organic light emitting diode (OLED), a liquid crystal display (LCD), a cathode ray tube display (CRT), an in-place switching (IPS) display, a touchscreen, etc.), a tactile output device, a printer and/or speakers(s). The interface circuit **1620** of the illustrated example, thus, typically includes a graphics driver card, a graphics driver chip and/or a graphics driver processor.

The interface circuit **1620** of the illustrated example also includes a communication device such as a transmitter, a receiver, a transceiver, a modem, a residential gateway, a wireless access point, and/or a network interface to facilitate exchange of data with external machines (e.g., computing devices of any kind) via a network **1626**, such as the WTSN **260**. The communication can be via, for example, an Ethernet connection, a digital subscriber line (DSL) connection, a telephone line connection, a coaxial cable system, a satellite system, a line-of-site wireless system, a cellular telephone system, etc. In this example, the interface circuit **1620** implements the example control-side receiver **250** and the example control-side transmitter **252**.

The processor platform **1600** of the illustrated example also includes one or more mass storage devices **1628** for storing software and/or data. Examples of such mass storage devices **1628** include floppy disk drives, hard drive disks, compact disk drives, Blu-ray disk drives, redundant array of independent disks (RAID) systems, and digital versatile disk (DVD) drives.

The machine executable instructions **1632** corresponding to the instructions of FIGS. **11**, **12** and/or **13** may be stored in the mass storage device **1628**, in the volatile memory **1614**, in the non-volatile memory **1616**, in the local memory **1613** and/or on a removable non-transitory computer readable storage medium, such as a CD or DVD **1636**.

FIG. **17** is a block diagram of an example processor platform **1700** structured to execute the instructions of FIG. **11** to implement target side processing in the example predictive wireless feedback control system **200** of FIGS. **2-3**. The processor platform **1700** can be, for example, a server, a personal computer, a workstation, a self-learning machine (e.g., a neural network), a mobile device (e.g., a cell phone, a smart phone, a tablet such as an iPad™), or any other type of computing device.

The processor platform **1700** of the illustrated example includes a processor **1712**. The processor **1712** of the illustrated example is hardware. For example, the processor **1712** can be implemented by one or more integrated circuits, logic circuits, microprocessors, GPUs, DSPs, or controllers from any desired family or manufacturer. The hardware processor **1712** may be a semiconductor based (e.g., silicon based) device. In this example, the processor **1712** implements the example actuator **220**, the example sensors **225**, the example MAC synchronizers **280** and **281**, the example transmit timestamper **282**, the example actuation link latency determiner **288** and the actuation link latency reporter **296**.

The processor **1712** of the illustrated example includes a local memory **1713** (e.g., a cache). The processor **1712** of the illustrated example is in communication with a main memory including a volatile memory **1714** and a non-volatile memory **1716** via a link **1718**. The link **1718** may be implemented by a bus, one or more point-to-point connections, etc., or a combination thereof. The volatile memory **1714** may be implemented by SDRAM, DRAM, RDRAM® and/or any other type of random access memory device. The non-volatile memory **1716** may be implemented by flash memory and/or any other desired type of memory device. Access to the main memory **1714**, **1716** is controlled by a memory controller.

The processor platform **1700** of the illustrated example also includes an interface circuit **1720**. The interface circuit **1720** may be implemented by any type of interface standard, such as an Ethernet interface, a USB, a Bluetooth® interface, an NFC interface, and/or a PCI express interface.

In the illustrated example, one or more input devices **1722** are connected to the interface circuit **1720**. The input device(s) **1722** permit(s) a user to enter data and/or commands into the processor **1712**. The input device(s) can be implemented by, for example, an audio sensor, a microphone, a camera (still or video), a keyboard, a button, a mouse, a touchscreen, a track-pad, a trackball, a trackbar (such as an isopoint), a voice recognition system and/or any other human-machine interface. Also, many systems, such as the processor platform **1700**, can allow the user to control the computer system and provide data to the computer using physical gestures, such as, but not limited to, hand or body movements, facial expressions, and face recognition.

One or more output devices **1724** are also connected to the interface circuit **1720** of the illustrated example. The output devices **1724** can be implemented, for example, by display devices (e.g., an LED, an OLED, an LCD, a CRT display, an IPS display, a touchscreen, etc.), a tactile output device, a printer and/or speakers(s). The interface circuit **1720** of the illustrated example, thus, typically includes a graphics driver card, a graphics driver chip and/or a graphics driver processor.

The interface circuit **1720** of the illustrated example also includes a communication device such as a transmitter, a receiver, a transceiver, a modem, a residential gateway, a wireless access point, and/or a network interface to facilitate exchange of data with external machines (e.g., computing devices of any kind) via a network **1726**, such as the WTSN **260**. The communication can be via, for example, an Ethernet connection, a DSL connection, a telephone line connection, a coaxial cable system, a satellite system, a line-of-site wireless system, a cellular telephone system, etc. In this example, the interface circuit **1720** implements the example target-side receiver **254** and the example target-side transmitter **256**.

The processor platform **1700** of the illustrated example also includes one or more mass storage devices **1728** for storing software and/or data. Examples of such mass storage devices **1728** include floppy disk drives, hard drive disks, compact disk drives, Blu-ray disk drives, RAID systems, and DVD drives.

The machine executable instructions **1732** corresponding to the instructions of FIG. **11** may be stored in the mass storage device **1728**, in the volatile memory **1714**, in the non-volatile memory **1716**, in the local memory **1713** and/or on a removable non-transitory computer readable storage medium, such as a CD or DVD **1736**.

From the foregoing, it will be appreciated that example methods, apparatus, systems and articles of manufacture (e.g., physical storage media) to implement wireless feedback control loops with neural networks to predict target system states have been disclosed. Disclosed examples improve the efficiency of using a computing device by enabling use of wireless networks to perform feedback control of target systems that are latency-sensitive and/or reliability-sensitive. Disclosed examples are accordingly directed to one or more improvement(s) in the functioning of a computer.

The foregoing disclosure provides example solutions to implement wireless feedback control loops with neural networks to predict target system states. The following further examples, which include subject matter such as a wireless feedback control system, a non-transitory computer readable medium including instructions that, when executed, cause at least one processor to implement a wireless feedback control system, and a wireless feedback control method, are disclosed herein. The disclosed examples can be implemented individually and/or in one or more combinations.

Example 1 is a wireless feedback control system including a receiver to receive a first measurement of a target system via a first wireless link. The wireless feedback control system of example 1 also includes a neural network to predict a value of a state of the target system at a future time relative to a prior time associated with the first measurement, a time interval between the prior time and the future time based on a first latency of the first wireless link and a second latency associated with a second wireless link. In example 1, the neural network is to predict the value of the state of the target system based on the first measurement and a prior sequence of values of a control signal previously generated to control the target system during the time interval between the prior time and the future time. In example 1, the neural network is to output the predicted value of the state of the target system to a controller to generate a new value of the control signal. The wireless feedback control system of example 1 further includes a transmitter to transmit the new value of the control signal to the target system via the second wireless link.

Example 2 includes the subject matter of example 1, wherein the receiver is a first receiver, the transmitter is a first transmitter, and the first wireless link and the second wireless link are implemented by a wireless time sensitive network that is to provide time synchronization between (i) the first receiver and a second transmitter that is to transmit the first measurement of the target system to the first receiver via the first wireless link, and (ii) the first transmitter and a second receiver that is to receive the new value of the control signal transmitted by the first transmitter via the second wireless link.

Example 3 includes the subject matter of example 2, wherein the first receiver is to receive the first measurement in a message from the second transmitter via the first wireless link, the message to include a timestamp to identify a first time at which the second transmitter transmitted the message, the first receiver to determine the first latency of the first wireless link based on the timestamp and a second time at which the first receiver received the message.

Example 4 includes the subject matter of example 2, wherein the first transmitter is to transmit a first one of the prior sequence of values of the control signal in a message to the second receiver via the second wireless link, the message to include a timestamp to identify a first time at which the first transmitter transmitted the message, the first transmitter to determine the second latency associated with the second wireless link based on a report from the second receiver in response to the message.

Example 5 includes the subject matter of example 4, wherein the second latency associated with the first wireless link corresponds to at least one of a maximum latency of the second wireless link, a minimum latency of the second wireless link, an average latency for the second wireless link, or a probabilistic latency value for the second wireless link.

Example 6 includes the subject matter of any one of examples 1 to 5, wherein the time interval between the prior time and the future time is sampled to include a first number of sample times, the predicted value of the state of the target system is a first predicted value, and the neural network includes a first neural network in communication with a second neural network, the first neural network trained to predict a second predicted value of the state of the target system based on the first measurement and a first one of the prior sequence of values of the control signal corresponding to a first sample time representative of the prior time, the second predicted value of the state of the target system corresponding to one sample time after the first sample time, and the second neural network to predict the first predicted value of the state of the target system based on the second predicted value of the state of the target system and remaining ones of the prior sequence of values of the control signal corresponding to ones of the first number of samples times after the first sample time.

Example 7 includes the subject matter of example 6, wherein the second neural network is to predict a plurality of predicted values of the state of the target system corresponding respectively to respective sample times between the second predicted value and the first predicted value, the second neural network to predict respective ones of the plurality of predicted values iteratively based on application of the remaining ones of the sequence of values of the control signal sequentially to the second neural network.

Example 8 includes the subject matter of any one of examples 1 to 7, and further includes a neural network updater to update the neural network based on an error between the first measurement and a delayed reference value representative of a target state of the target system corresponding to the prior time associated with the first measurement.

Example 9 is a non-transitory computer readable medium including computer readable instructions which, when executed, cause at least one processor to at least: (i) execute a neural network to predict a value of a state of a target system at a future time relative to a prior time associated with a first measurement of the target system obtained via a first wireless link, a time interval between the prior time and the future time based on a first latency of the first wireless link and a second latency associated with a second wireless link, the neural network to predict the value of the state of the target system based on the first measurement and a prior sequence of values of a control signal previously generated to control the target system during the time interval between the prior time and the future time; and (ii) output the predicted value of the state of the target system to a controller that is to generate a new value of the control signal that is to be sent to the target system via the second wireless link.

Example 10 includes the subject matter of example 9, wherein the time interval between the prior time and the future time is sampled to include a first number of sample times, the predicted value of the state of the target system is a first predicted value, and to execute the neural network, the computer readable instructions, when executed, cause the at least one processor to: (i) execute a first neural network to predict a second predicted value of the state of the target system based on the first measurement and a first one of the prior sequence of values of the control signal corresponding to a first sample time representative of the prior time, the second predicted value of the state of the target system corresponding to one sample time after the first sample time; and (ii) execute a second neural network to predict the first predicted value of the state of the target system based on the second predicted value of the state of the target system and remaining ones of the sequence of values of the control signal corresponding to ones of the first number of samples times after the first sample time.

Example 11 includes the subject matter of example 10, wherein the computer readable instructions, when executed, cause the at least one processor to execute the second neural network to predict a plurality of predicted values of the state of the target system corresponding respectively to respective sample times between the second predicted value and the first predicted value, the instructions, when executed, to cause the at least one processor to execute the second neural network to predict respective ones of the plurality of predicted values iteratively based on application of the remaining ones of the sequence of values of the control signal sequentially to the second neural network.

Example 12 includes the subject matter of any one of examples 9 to 11, wherein the computer readable instructions, when executed, further cause the at least one processor to update the neural network based on an error between the first measurement and a delayed reference value representative of a target state of the target system corresponding to the prior time associated with the first measurement.

Example 13 is a wireless feedback control method including accessing a first measurement of a target system received via a first wireless link. Example 13 also includes predicting, with a neural network, a value of a state of the target system at a future time relative to a prior time associated with the first measurement, a time interval between the prior time and the future time based on a first latency of the first wireless link and a second latency associated with a second wireless link, the predicting of the value of the state of the target system based on the first measurement and a prior sequence of values of a control signal previously generated to control the target system during the time interval between the prior time and the future time. Example 13 further includes outputting the predicted value of the state of the target system to a controller that is to generate a new value of the control signal, and sending the new value of the control signal to the target system via the second wireless link.

Example 14 includes the subject matter of example 13, wherein the first wireless link and the second wireless link are implemented by a wireless time sensitive network.

Example 15 includes the subject matter of example 13 or example 14, and further includes (i) receiving the first measurement in a message via the first wireless link, the message to include a timestamp to identify a first time at which the message was transmitted; and (ii) determining the first latency of the first wireless link based on the timestamp and a second time at which the message was received.

Example 16 includes the subject matter of any one of examples 13 to 15, and further includes (i) transmitting a first one of the prior sequence of values of the control signal in a message via the second wireless link, the message to include a timestamp to identify a first time at which the message was transmitted; and (ii) determining the second latency associated with the second wireless link based on a report received in response to the message.

Example 17 includes the subject matter of example 16, wherein the second latency associated with the first wireless link corresponds to at least one of a maximum latency of the second wireless link, a minimum latency of the second wireless link, an average latency for the second wireless link, or a probabilistic latency value for the second wireless link.

Example 18 includes the subject matter of any one of examples 13 to 17, wherein the time interval between the prior time and the future time is sampled to include a first number of sample times, the predicted value of the state of the target system is a first predicted value, the neural network includes a first neural network in communication with a second neural network, and the predicting the value of the state of the target system includes: (i) predicting, with the first neural network, a second predicted value of the state of the target system based on the first measurement and a first one of the prior sequence of values of the control signal corresponding to a first sample time representative of the prior time, the second predicted value of the state of the target system corresponding to one sample time after the first sample time; and (ii) predicting, with the second neural network, the first predicted value of the state of the target system based on the second predicted value of the state of the target system and remaining ones of the sequence of values of the control signal corresponding to ones of the first number of samples times after the first sample time.

Example 19 includes the subject matter of example 18, wherein the predicting with the second neural network includes predicting, with the second neural network, a plurality of predicted values of the state of the target system corresponding respectively to respective sample times between the second predicted value and the first predicted value, the second neural network to predict respective ones of the plurality of predicted values iteratively based on application of the remaining ones of the sequence of values of the control signal sequentially to the second neural network.

Example 20 includes the subject matter of any one of examples 13 to 19, and further includes updating the neural network based on an error between the first measurement and a delayed reference value representative of a target state of the target system corresponding to the prior time associated with the first measurement.

Example 21 is a wireless feedback control system including means for receiving a first measurement of a target system via a first wireless link. The wireless feedback control system of example 21 also includes means for predicting a value of a state of the target system at a future time relative to a prior time associated with the first measurement, a time interval between the prior time and the future time based on a first latency of the first wireless link and a second latency associated with a second wireless link, the means for predicting to predict the value of the state of the target system based on the first measurement and a prior sequence of values of a control signal previously generated to control the target system during the time interval between the prior time and the future time, the means for predicting to output the predicted value of the state of the target system to a controller to generate a new value of the control signal. The wireless feedback control system of example 21 further includes means for transmitting the new value of the control signal to the target system via the second wireless link.

Example 22 includes the subject matter of example 21, wherein the time interval between the prior time and the future time is sampled to include a first number of sample times, and the predicted value of the state of the target system is a first predicted value. The means for predicting of example 22 includes first neural network means for predicting a second predicted value of the state of the target system based on the first measurement and a first one of the prior sequence of values of the control signal corresponding to a first sample time representative of the prior time, the second predicted value of the state of the target system corresponding to one sample time after the first sample time. The means for predicting of example 22 also includes second neural network means for predicting the first predicted value of the state of the target system based on the second predicted value of the state of the target system and remaining ones of the sequence of values of the control signal corresponding to ones of the first number of samples times after the first sample time.

Example 23 includes the subject matter of example 22, wherein the second neural network means is to predict a plurality of predicted values of the state of the target system corresponding respectively to respective sample times between the second predicted value and the first predicted value, the second neural network means to predict respective ones of the plurality of predicted values iteratively based on application of the remaining ones of the sequence of values of the control signal sequentially to the second neural network.

Example 24 includes the subject matter of any one of examples 21 to 23, and further includes means for updating the means for predicting based on an error between the first measurement and a delayed reference value representative of a target state of the target system corresponding to the prior time associated with the first measurement.

Although certain example methods, apparatus and articles of manufacture have been disclosed herein, the scope of coverage of this patent is not limited thereto. On the contrary, this patent covers all methods, apparatus and articles of manufacture fairly falling within the scope of the claims of this patent.

What is claimed is:

1. A wireless feedback control system comprising:

a receiver to receive a first measurement of a target system via a first wireless link;

a first neural network and a second neural network to:

predict a future value of a state of the target system corresponding to a future time relative to a prior time associated with the first measurement, a time interval between the prior time and the future time based on a first latency associated with the first wireless link and a second latency associated with a second wireless link, the first neural network to predict an initial value of the state of the target system based on the first measurement and a first one of a sequence of prior values of a control signal previously generated to control the target system during the time interval between the prior time and the future time, the second neural network to predict intermediate values and the future value of the state of the target system iteratively based on the initial value predicted by the first neural network and remaining ones of the sequence of prior values of the control signal, the second neural network to operate at a faster rate than the first neural network to cause the second neural network to perform a first number of predictor prediction iterations during a time interval in which the first neural network is to perform a single observer prediction iteration, the first number of predictor prediction iterations based on a sum of the first latency and the second latency; and

output the predicted future value of the state of the target system to a controller to generate a new value of the control signal; and

a transmitter to transmit the new value of the control signal to the target system via the second wireless link.

2. The wireless feedback control system of claim **1**, wherein the receiver is a first receiver, the transmitter is a first transmitter, and the first wireless link and the second wireless link are implemented by a wireless time sensitive network that is to provide time synchronization between (i) the first receiver and a second transmitter that is to transmit the first measurement of the target system to the first receiver via the first wireless link, and (ii) the first transmitter and a second receiver that is to receive the new value of the control signal transmitted by the first transmitter via the second wireless link.

3. The wireless feedback control system of claim **2**, wherein the first receiver is to receive the first measurement in a message from the second transmitter via the first wireless link, the message to include a timestamp to identify a first time at which the second transmitter transmitted the message, the first receiver to determine the first latency associated with the first wireless link based on the timestamp and a second time at which the first receiver received the message.

4. The wireless feedback control system of claim **2**, wherein the first transmitter is to transmit the first one of the sequence of prior values of the control signal in a message to the second receiver via the second wireless link, the message to include a timestamp to identify a first time at which the first transmitter transmitted the message, the first transmitter to determine the second latency associated with the second wireless link based on a report from the second receiver in response to the message.

5. The wireless feedback control system of claim 4, wherein the second latency associated with the second wireless link corresponds to at least one of a maximum latency of the second wireless link, a minimum latency of the second wireless link, an average latency for the second wireless link, or a probabilistic latency value for the second wireless link.

6. The wireless feedback control system of claim 1, wherein the time interval between the prior time and the future time is sampled to include a first number of sample times, the first one of the sequence of prior values of the control signal corresponds to a first sample time representative of the prior time, the predicted initial value of the state of the target system corresponds to one sample time after the first sample time, and the remaining ones of the sequence of prior values of the control signal correspond to ones of the first number of samples times after the first sample time.

7. The wireless feedback control system of claim 6, wherein the second neural network is to predict the intermediate values of the state of the target system to correspond respectively to respective sample times between the predicted initial value and the predicted future value, the second neural network to predict respective ones of the intermediate values and the future value iteratively based on application of the remaining ones of the sequence of prior values of the control signal sequentially to the second neural network.

8. The wireless feedback control system of claim 1, further including a neural network updater to update at least one of the first neural network or the second neural network based on an error between the first measurement and a delayed reference value representative of a target state of the target system corresponding to the prior time associated with the first measurement.

9. At least one non-transitory computer readable medium comprising computer readable instructions which, when executed, cause at least one processor to at least:

execute a first neural network and a second neural network to predict a future value of a state of a target system corresponding to a future time relative to a prior time associated with a first measurement of the target system obtained via a first wireless link, a time interval between the prior time and the future time based on a first latency associated with the first wireless link and a second latency associated with a second wireless link, the first neural network to predict an initial value of the state of the target system based on the first measurement and a first one of a sequence of prior values of a control signal previously generated to control the target system during the time interval between the prior time and the future time, the second neural network to predict intermediate values and the future value of the state of the target system iteratively based on the initial value predicted by the first neural network and remaining ones of the sequence of prior values of the control signal, the second neural network to operate at a faster rate than the first neural network to cause the second neural network to perform a first number of predictor prediction iterations during a time interval in which the first neural network is to perform a single observer prediction iteration, the first number of predictor prediction iterations based on a sum of the first latency and the second latency; and

output the predicted future value of the state of the target system to a controller that is to generate a new value of the control signal that is to be sent to the target system via the second wireless link.

10. The at least one non-transitory computer readable medium of claim 9, wherein the time interval between the prior time and the future time is sampled to include a first number of sample times, the first one of the sequence of prior values of the control signal corresponds to a first sample time representative of the prior time, the predicted initial value of the state of the target system corresponds to one sample time after the first sample time, and the remaining ones of the sequence of prior values of the control signal correspond to ones of the first number of samples times after the first sample time.

11. The at least one non-transitory computer readable medium of claim 10, wherein the computer readable instructions are to cause the at least one processor to execute the second neural network to predict the intermediate values of the state of the target system to correspond respectively to respective sample times between the predicted initial value and the predicted future value, the second neural network to predict respective ones of the intermediate values and the future value iteratively based on application of the remaining ones of the sequence of prior values of the control signal sequentially to the second neural network.

12. The at least one non-transitory computer readable medium of claim 9, wherein the computer readable instructions are to cause the at least one processor to update at least one of the first neural network or the second neural network based on an error between the first measurement and a delayed reference value representative of a target state of the target system corresponding to the prior time associated with the first measurement.

13. A wireless feedback control method comprising:

accessing a first measurement of a target system received via a first wireless link;

predicting, with a first neural network and a second neural network, a future value of a state of the target system corresponding to a future time relative to a prior time associated with the first measurement, a time interval between the prior time and the future time based on a first latency associated with the first wireless link and a second latency associated with a second wireless link, the predicting of the future value of the state of the target system including (i) predicting, with the first neural network, an initial value of the state of the target system based on the first measurement and a first one of a sequence of prior values of a control signal previously generated to control the target system during the time interval between the prior time and the future time, and (ii) predicting, with the second neural network, intermediate values and the future value of the state of the target system iteratively based on the initial value predicted by the first neural network and remaining ones of the sequence of prior values of the control signal, the second neural network to operate at a faster rate than the first neural network to cause the second neural network to perform a first number of predictor prediction iterations during a time interval in which the first neural network is to perform a single observer prediction iteration, the first number of predictor prediction iterations based on a sum of the first latency and the second latency;

outputting the predicted future value of the state of the target system to a controller that is to generate a new value of the control signal; and

sending the new value of the control signal to the target system via the second wireless link.

14. The method of claim 13, wherein the first wireless link and the second wireless link are implemented by a wireless time sensitive network.

15. The method of claim 13, further including:

receiving the first measurement in a message via the first wireless link, the message to include a timestamp to identify a first time at which the message was transmitted; and

determining the first latency associated with the first wireless link based on the timestamp and a second time at which the message was received.

16. The method of claim 13, further including:

transmitting the first one of the sequence of prior values of the control signal in a message via the second wireless link, the message to include a timestamp to identify a first time at which the message was transmitted; and

determining the second latency associated with the second wireless link based on a report received in response to the message.

17. The method of claim 16, wherein the second latency associated with the second wireless link corresponds to at least one of a maximum latency of the second wireless link, a minimum latency of the second wireless link, an average latency for the second wireless link, or a probabilistic latency value for the second wireless link.

18. The method of claim 13, wherein the time interval between the prior time and the future time is sampled to include a first number of sample times, the first one of the sequence of prior values of the control signal corresponds to a first sample time representative of the prior time, the predicted initial value of the state of the target system corresponds to one sample time after the first sample time, and the remaining ones of the sequence of prior values of the control signal correspond to ones of the first number of samples times after the first sample time.

19. The method of claim 18, wherein the predicting with the second neural network includes predicting, with the second neural network, the intermediate values of the state of the target system to correspond respectively to respective sample times between the predicted initial value and the predicted future value, the second neural network to predict respective ones of the intermediate values and the future value iteratively based on application of the remaining ones of the sequence of prior values of the control signal sequentially to the second neural network.

20. The method of claim 13, further including updating at least one of the first neural network or the second neural network based on an error between the first measurement and a delayed reference value representative of a target state of the target system corresponding to the prior time associated with the first measurement.

21. A wireless feedback control system comprising:

means for receiving a first measurement of a target system via a first wireless link;

means for predicting a future value of a state of the target system corresponding to a future time relative to a prior time associated with the first measurement, a time interval between the prior time and the future time based on a first latency associated with the first wireless link and a second latency associated with a second wireless link, the means for predicting including (i) first neural network means for predicting an initial value of the state of the target system based on the first measurement and a first one of a sequence of prior values of a control signal previously generated to control the target system during the time interval between the prior time and the future time, and (ii) second neural network means for predicting intermediate values and the future value of the state of the target system iteratively based on the initial value predicted by the first neural network means and remaining ones of the sequence of prior values of the control signal, the second neural network means to operate at a faster rate than the first neural network means to cause the second neural network means to perform a first number of predictor prediction iterations during a time interval in which the first neural network means is to perform a single observer prediction iteration, the first number of predictor prediction iterations based on a sum of the first latency and the second latency, the means for predicting to output the predicted future value of the state of the target system to a controller to generate a new value of the control signal; and

means for transmitting the new value of the control signal to the target system via the second wireless link.

22. The wireless feedback control system of claim 21, wherein the time interval between the prior time and the future time is sampled to include a first number of sample times, the first one of the sequence of prior values of the control signal corresponds to a first sample time representative of the prior time, the predicted initial value of the state of the target system corresponds to one sample time after the first sample time, the remaining ones of the sequence of prior values of the control signal correspond to ones of the first number of samples times after the first sample time.

23. The wireless feedback control system of claim 22, wherein the second neural network means is to predict the intermediate values of the state of the target system to correspond respectively to respective sample times between the predicted initial value and the predicted future value, the second neural network means to predict respective ones of the intermediate values and the future value iteratively based on application of the remaining ones of the sequence of prior values of the control signal sequentially to the second neural network means.

24. The wireless feedback control system of claim 21, further including means for updating the means for predicting based on an error between the first measurement and a delayed reference value representative of a target state of the target system corresponding to the prior time associated with the first measurement.

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